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THE USE OF EEG AS A WORKLOAD ASSESSMENT TOOL IN FLIGHT TEST

BRUCE P. HUNN
Project Manager

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OCTOBER 1993

TECHNICAL INFORMATION MANUAL

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AIR FORCE FLIGHT TEST CENTER
EDWARDS AIR FORCE BASE, CALIFORNIA
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UNITED STATES AIR FORCE

REPORT DOCUMENTATION PAGE

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Technical Manual

The use of EEG as a Workload Assessment Tool in Flight Test

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This report examines the use of EEG (Electroencephalography) as a tool to assess aircrew mental workload in-flight. It contains a brief history of EEG methods and a detailed analysis section. It also contains a large reference section for additional research purposes. Analysis methods, both historical and current are discussed. Statistical and graphic presentation of continuous EEG data is reviewed and recommendations are made for future testing of EEG technologies.

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EEG, Electroencephalography, Physiological measures Workload, Test and Evaluation

The Use of EEG as a Workload Assessment Tool in Flight Test

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USAF/AFFTC
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PREFACE

This Technical Information Memorandum was written to inform Air Force Flight Test Center (AFFTC) Human Factors Engineers and other interested parties of the history, hardware, and analysis methodology involved with the use of EEG technologies. The flight test center has been involved with the measurement of EEG since the 1980's when Dr. M.B. Sterman's University of California at Los Angeles (UCLA) team first began to perform in-flight EEG recording on AFFTC flights at Edwards Air Force Base. That beginning led to the establishment of the In-flight Physiology Test Program (IFP), of which the author is project manager. The IFP seeks to explore the use of physiological measurements of aircrew as a tool to assess task loading and mental and physical effort. The measurement and quantification of workload is the primary goal of this program; and with that goal in mind the integrated collection of subjective, performance and physiological data are being accomplished. During the last 3 years, interest in EEG technology has increased dramatically and several EEG programs have developed within different organizations of the AFFTC.

The 412 Operations Group/DOEH (Human Factors) sponsored the effort required to prepare this Technical Information Memorandum. The author wishes to express sincere appreciation to Mrs. Deborah Mummah, 412 OG/DOEH. Thanks are extended to Drs. Barry Sterman and Chris Mann, from UCLA and Lawrence Ames of the the 412 Operations Group DOEH for their valuable guidance and review of this document. Information and experimental data for this study were provided by Mr. Brandal Suyenobu, Mr. David Kaiser, and Ms. Bettina Veigel of UCLA. Data from the AFFTC/Test Pilot School/NT-33 EEG study were provided by Major Pete Demitry of the AFTI F-16 Program. In addition, many thanks are extended to Dr. Glen Wilson of the USAF Armstrong Laboratory who provided information and prepublication documents which contributed significantly to this research effort.

EXECUTIVE SUMMARY

This report examines electroencephalography (EEG) as a process to assess aircrew task performance and workload. A historical review is made of the measurement and analysis of EEG data, as well as a review of current Air Force Flight Test Center (AFFTC) EEG flight studies. Information for this report is drawn from the AFFTC In-flight Physiology Project (IFP), the AFFTC NT-33 TPS/EEG project, Dr. M.B. Sterman's UCLA/AFFTC EEG team's work and an EEG workload literature review. The report also covers EEG measurement hardware and signal analysis challenges. This report evaluates several EEG analysis methodologies used in the general EEG literature and recommends analysis methods for future studies at the flight test center. Quantitative and qualitative assessments of EEG data are discussed and statistical methods of EEG interpretation are examined in detail. A large bibliographic reference is included for further EEG, workload, and workload assessment information purposes.

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BACKGROUND

This technical information manual (TIM) presents the results of an Air Force Flight Test Center (AFFTC) effort to examine the use of electroencephalography (EEG) technologies for the assessment of aircrew workload during the flight testing of aircraft. Information for this publication was collected through literature searches and lessons learned from EEG test programs at the AFFTC.

Workload as defined in this publication is a complex concept which involves primarily mental effort, but also the associated factors of physical actions and environmental variables. This study will focus on applications to the flight environment. In that environment there is no simple division of mental versus physical tasks, and consequently, the effort of measuring workload will take a global approach.

Assessment of workload has traditionally been performed with the use of two primary tools, subjective inquiry and performance comparisons. Subjective inquiry has been the dominant tool in AFFTC flight test and has been primarily of two varieties, postflight questionnaires and in-flight ratings. There is considerable overlap within these two divisions and, in fact, the same tools have been used both in the air and on the ground. Questionnaires have involved interview techniques such as narrative descriptions, the use of rating scales, and subjective opinion reports. In-flight subjective measures have largely been in the form of verbal rating scale assessments using a variety of scales. Rating scales such as Subjective Workload Assessment Technique (SWAT), Subjective Workload Dominance (SWORD), and NASA Task Load Index (TLX) have led the field in the subjective assessment of workload.

Performance assessment has also been used to determine workload, such as in flight test where comparative analyses of pilot flight performance parameters are compared. Under controlled conditions, often using the pilot as his own control, performance has been compared using criterion such as flight path deviation, altitude control, approach and departure deviations, and other objective performance data. Changes in performance are then correlated with the demands of individual missions to determine whether the workload level affected the performance of the aircraft-pilot system.

The previous subjective assessment tools have some disadvantages. Subjective methods often have great variablity within and between subjects and are susceptible to complex response biasing, while performance measures are very difficult to reproduce and offer challenges in the control of extraneous variables. In-flight subjective measures also suffer from being fairly intrusive to the primary task of flying the aircraft. The use of pilot performance methods may also be subject to high variability due to environmental conditions beyond the control of the experimenter.

OBJECTIVES

The primary purpose of this TIM was to investigate the feasability of EEG as an inflight Human Factors workload assessment tool and to assess its usefulness in projects undertaken at the AFFTC. The following discussion section covers historical EEG background information and current AFFTC research. The secondary focus of this report will be on the analysis methodology used historically and currently on EEG data.

DISCUSSION

Workload and EEG.

Workload as defined in this report represents both physical and mental effort. Mental workload is complex and cannot be completely separated from physical tasks. Nearly all aspects of mental workload in aircraft flight have their corresponding physical control actions, therefore, any tasks performed in a flight scenario will have a physical component which is associated with a mental process. The use of the term workload implies both physical and mental aspects and for the purposes of this report will be used synonymously. The use of workload measures inflight implies mixtures of complex physical and mental tasking. One initial assumption made is if a task or task segment is considered by the subject to be more difficult, then it is assumed that the subjects level of workload is increased.

Since any conception of mental or physical workload is based on the ability of the brain to coordinate the body, a logical assumption would be that workload could be tapped by some direct connection with the brain. This has previously been attempted by the use of subjective methods such as interview, questionnaire, and rating systems. These systems provide varying perspectives on how much "workload" the individual is experiencing. The advantages to these systems are associated with their ease of use, their ability to quantify thought, and the fact that they can provide specific psychological and motivational insight to actions. Their primary disadvantage is that this type of communication is subject to the individual subject's conscious filtering of the data for a variety of psychological reasons. All of the primary emotional constructs of the human being are incorporated into their response to subjective questions. For example, a question response will be filtered by psychological and physical factors, so that the response to an identical question after a 1 hour flight and after a 12 hour flight will probably differ simply on the basis of fatigue. This filtering is a conscious action which can usually be controlled, but not entirely suppressed. One driving factor in the use of physiological measures, EEG in particular, is the perception that such measures are not subject to direct conscious control, and therefore are less susceptible to biasing effects. It is with this thought that physiological measures tap the source of cognition, without the filter of consciousness, and this concept appeals to many physiological researchers.

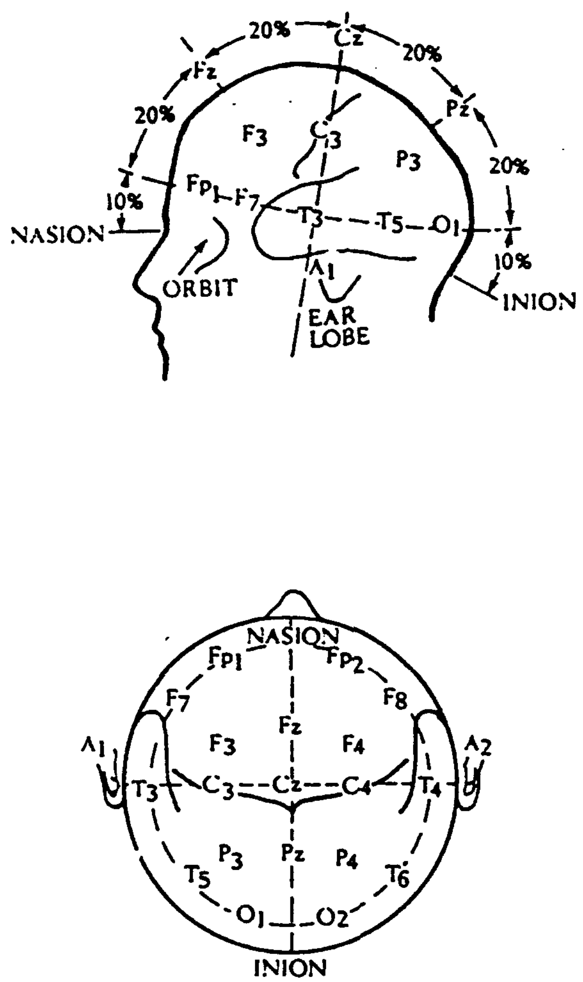
Many physiological measures have been proposed to assess human workload abilities. Electrocardiograms, Eye Blinks, Galvanic Skin Response, Respiration, Pupil Response, and Speech Signals have all been tested to some degree. The EEG is intuitively appealing, since it tracks the source of cognition and has a very quick response time potential. The correl^tion of EEG signals to behavioral actions is of the most complex nature and not subject to easy interpretation. The following sections will detail the attempts to use EEG information to quantify mental effort and consequently, workload.

EEG History

The measurement of EEG is not as recent a science as might be supposed. As early as the 1890's, Caton was measuring the EEG signal with very primative electrodes and recording equipment. Berger examined changes in the 8 to 12 Hertz (Hz) band of the EEG signal in the 1930's. As early as 1949, Morruzzi and Magoun postulated that cortical arousal (activation) would increase with increasing "workload" and that manifestation would be present as a lowered voltage, higher frequency, EEG pattern. This pattern is referred to as an alpha supression, where the normal rhythmic alpha pattern in the 8 to 12 Hz range is suppressed or modified in frequency and amplitude.

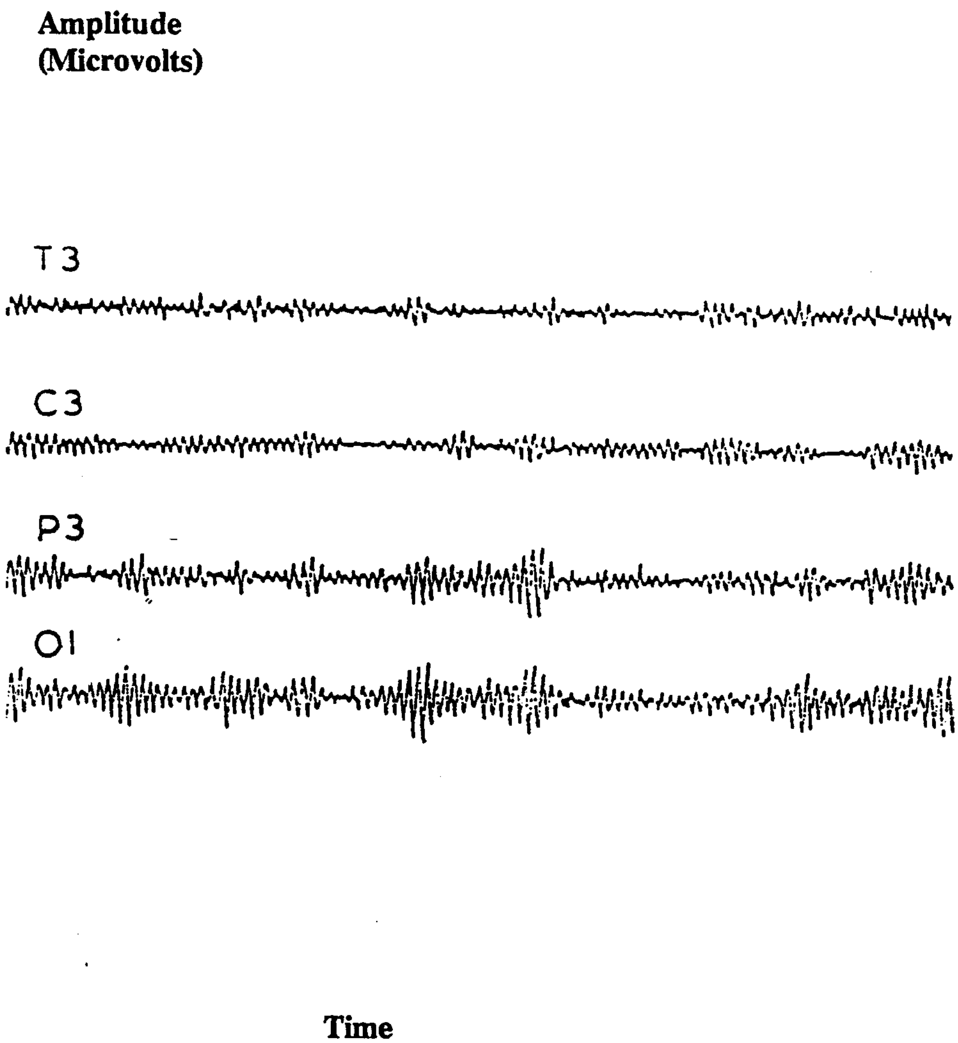
More recently, Lindsley (1952), Hebb, (1955) and Duffy (1962) postulated that EEG activation (and, consequently alpha suppression) may follow a continuum much like that found in behavioral arousal. These theorys are based on the widely reported cyclic properties of the alpha band waveform.

With the increase in sophistication of measurement technologies, the measurement of brain "electrical output" has changed dramatically over the last 30 years, for example; the technology of the 1940's represented limited numbers of measurement sites, mechanical pen type recording, and no on-line analysis abilities. In contrast, current technologies allow multiple site monitoring (see Figure 1) with on-line Fast Fourier Transform (FFT) capabilities, and digitized data storage in the gigabyte range. Additionally, computers can create spectral and topographic EEG landscapes, which indicate data output by site within any bandwidth. This dramatic evolution in technique may have outstripped the analysis capabilities previously used for earlier investigations (see Figure 2) and it is with that consideration that this report will emphasize the complexity of the problem and some possible means of creating a "physiological workload" metric.



Side view and top view of the head showing electrode placement based on cranial anthropometry. The nasion is also known as the sellion, while the letters stand for corresponding areas of the brain, F = frontal, C = central, T = temporal, P = parietal, O = occiptal.

Figure 1 Electrode Site Locations



Demonstration of the output of several sites, the output of which has been band filtered. Four channels are shown.

Figure 2 Brainwave Output by Site

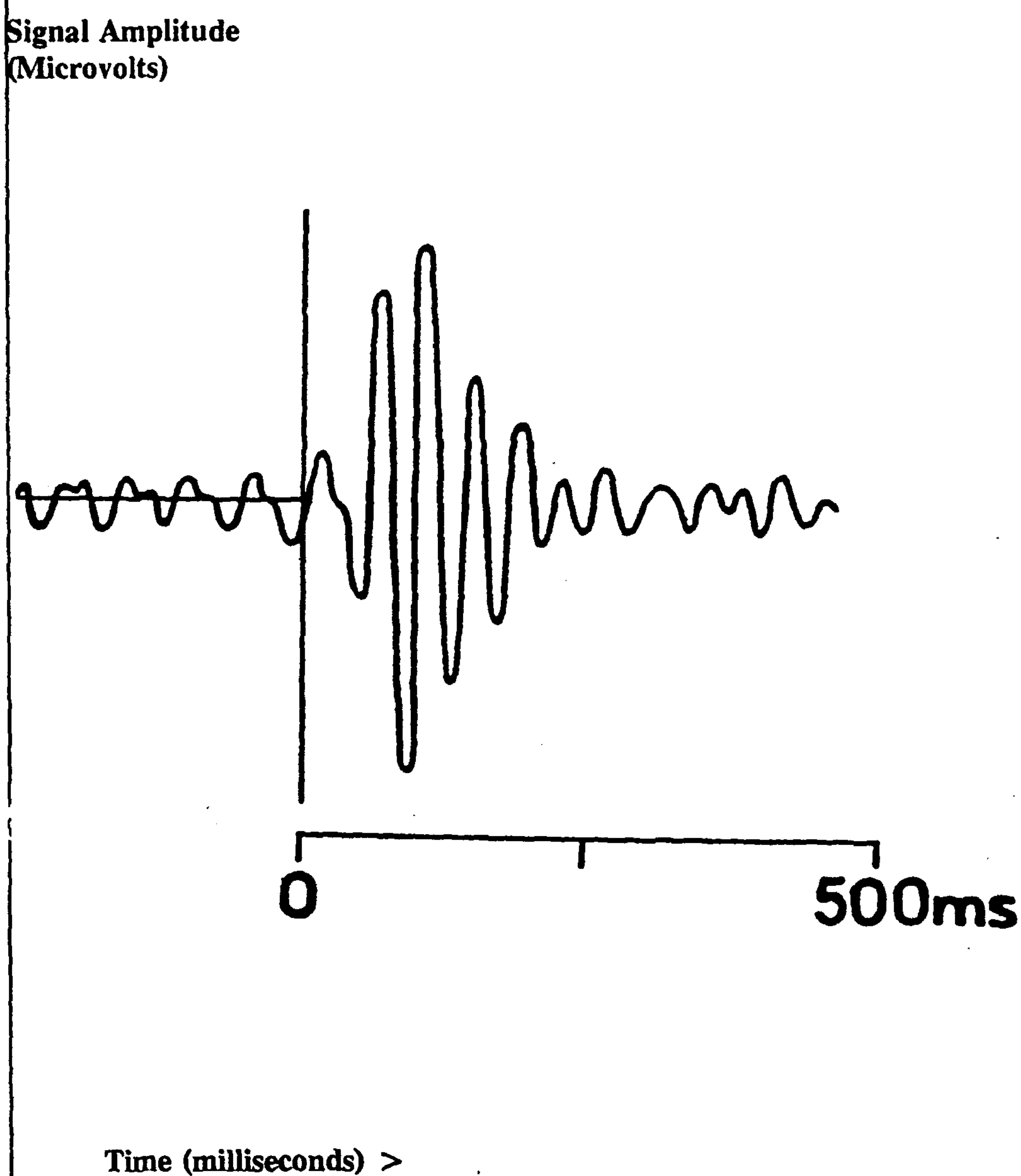
EEG Signal Research

Evoked Potentials

The application of EEG technology to workload, principally aircrew workload, occurred in the late 1960's to 1970's. Prior to that time the use of EEG had been primarily a medical tool with limited application to workload testing. Early military research in the 1960's and 1970's focused on training and selection criteria as well as performance decrement (due to a reduction in vigilance). The EEG data obtained at that time were based on the brains reaction to brief visual stimuli. These stimuli caused what was referred to as an evoked potential, that is, an event related electrical output. Researchers produced those evoked potentials (EPs) or event related potentials (ERPs) by flashing a bright light into the subject's eyes and the resultant responses, in terms of voltage changes, were recorded with scalp-mounted electrodes. Electrodes registered the brains electrical changes at scalp locations (also known as sites). The actual cause, formation and propagation of these electrical signals, is beyond the scope of this report, however, from an engineering perspective they can be recorded and analysed as representative traces of mental activity for any given type of task.

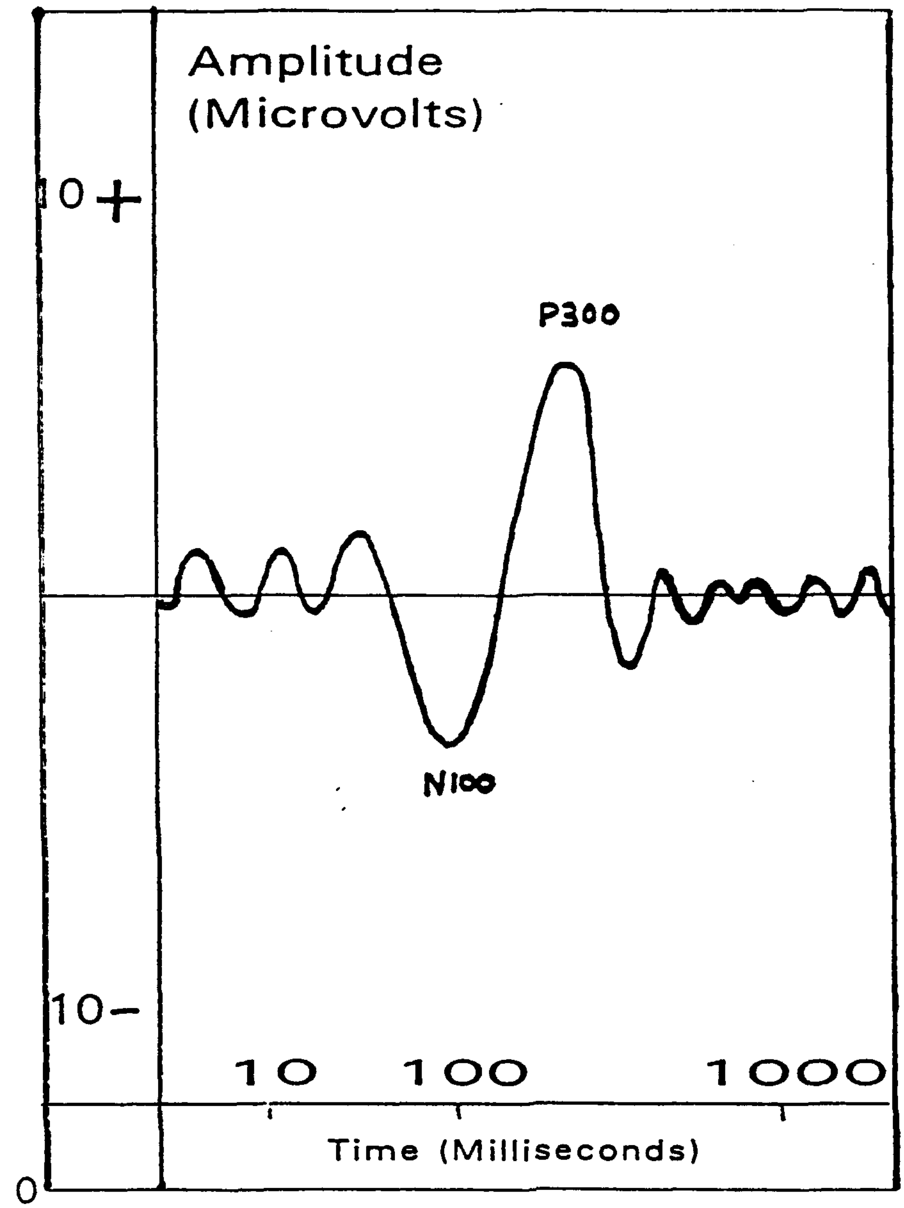
Evoked potentials produced by various stimuli consist of two components, which are time related, they are: exogenous and endogenous. Exogenous components are sensitive to stimulus duration, intensity, and frequency, and occur with short <100 milisecond (ms) latencies. They are relatively insensitive to task demand levels and have wide variance with different stimulus modalities, however, they have little variance (<25 ms) within individual subjects. Endogenous components occur after a 100 ms cutoff and vary with task relevance, expectancy, and difficulty. Figure 3 shows how the continuous EEG signal is modified by the stimulus (bright light flash) and results in the various EP components with the passage of time. The brain reacts to the stimulus flash with a large amplitude transient response that contains positive and negative components which are shown in Figure 4. These components are named P or N (positive or negative) followed by their latency in ms (100 = 100 ms), therefore, P100 is a positive deflection at 100 ms post stimulus. The progression of the EP waveform with time also reflects the direction from sensory to processing and finally to motor activity in response to the stimulus.

There are several types of stimuli which have been used for EP research. These are succinctly described by Shearer, et al. (1984), and consist of visual, auditory, and somatosensory stimuli. Visual Evoked Potentials (VEPs) are elicited by strobes, pattern onset and offset, pattern reversal, or pattern shifts. Auditory ERPs can be produced by clicks or tones, and may also be called Brainstem Auditory Evoked Potentials (BAEPs). Somatosensory Evoked Potentials (SEPs) are caused by electrical stimulation of median and tibial nerves.



The continuous, normal EEG signal, modified by a stimulus at time O, creates an Evoked Potential (EP), and then returns to the normal EEG waveform.

Figure 3 EEG to EP Transitions (ms)



The effect of a stimulus on the EEG. Sensory components are operating in the range from 0 to 200 ms. Processing components from 200 to 500 ms and motor components from 500 ms onward. Negative components may be shown at either the top or the bottom of the graph in normal practice. Both polarities of components are designated by a number following the polarity of the signal, i.e. N100 is a negative point 100 milliseconds after the stimulus onset.

Figure 4 Components of the EP Signal

A significant feature of EP analysis is that the EP signal produced by the brain is embedded in the continuous, but lower power, EEG signal. When EP studies are performed, the EP signal may be presented 20 to 100 times and then time averaged from the stimulus onset. Effectively this cancels out the ongoing EEG signal and allows the EP to be studied without the "noise" of the background EEG components. There is some controversy as to whether this cancellation of the background EEG signal is not creating an artificial brain signal based on EP output rather than "normal" EEG output. Wilson (1982) found problems in A-10 aircraft simulator testing where moderate to high workload conditions resulted in failures to attend to the EP tonal signal. His observations may have led to Biferno using a "relevant, naturally occurring eliciting stimuli" as an auditory EP producer in his 1985 study. Biferno's EP stimuli was the subject's radio call sign, which Wilson applauded as a reduction in the "artificial" nature of most EP stimuli which had previously been used. About this time the terminology for EPs switched to Event Related Potentials which reflected the change from simple light or tonal impulses to task related stimuli of various modalities.

Research issues within EP testing moved to specific components of brainwaves in the late 1970's through 1980's. Research by Isreal, Chesney, Wickens and Donchin, in 1980, used a tonal signal, instead of the more common visual stimulus, to assess the voltage output while performing a primary task. While performing the primary task (an air traffic control tracking situation) the tonal signal was presented and its consequent effect on the EEG signal was measured. This signal change (output voltage difference) was most noticeable about 300 ms after the tonal stimulus presentation. The designation of this 300-ms component was P300, meaning a positive voltage output 300 ms after the stimulus presentation. In addition, there were other components such as N100 and N200 that refer to negative amplitudes after simulus onset at 100 and 200 ms.

Natani and Gomer used a tonal EP, in 1981, to attempt to show significant P300 reductions and longer latencies with high workload conditions, however, this result was not replicated in additional trials. Generally, these recognition trials involved two secondary tones which had a probability of occurance of 80 percent or 20 percent. In all cases, the tone with the lower probability was the test point and had to be recognized and responded to in short term memory or with a button push.

Additional researchers associated with EPs such as Kramer, Wickens, and Donchin reported, in 1983, the association of a particular time-related element of brainwaves with increasing workload levels. This time component was referred to as the P300 potential and coincided with the voltage output 300 ms after a discrete tonal stimulus event.

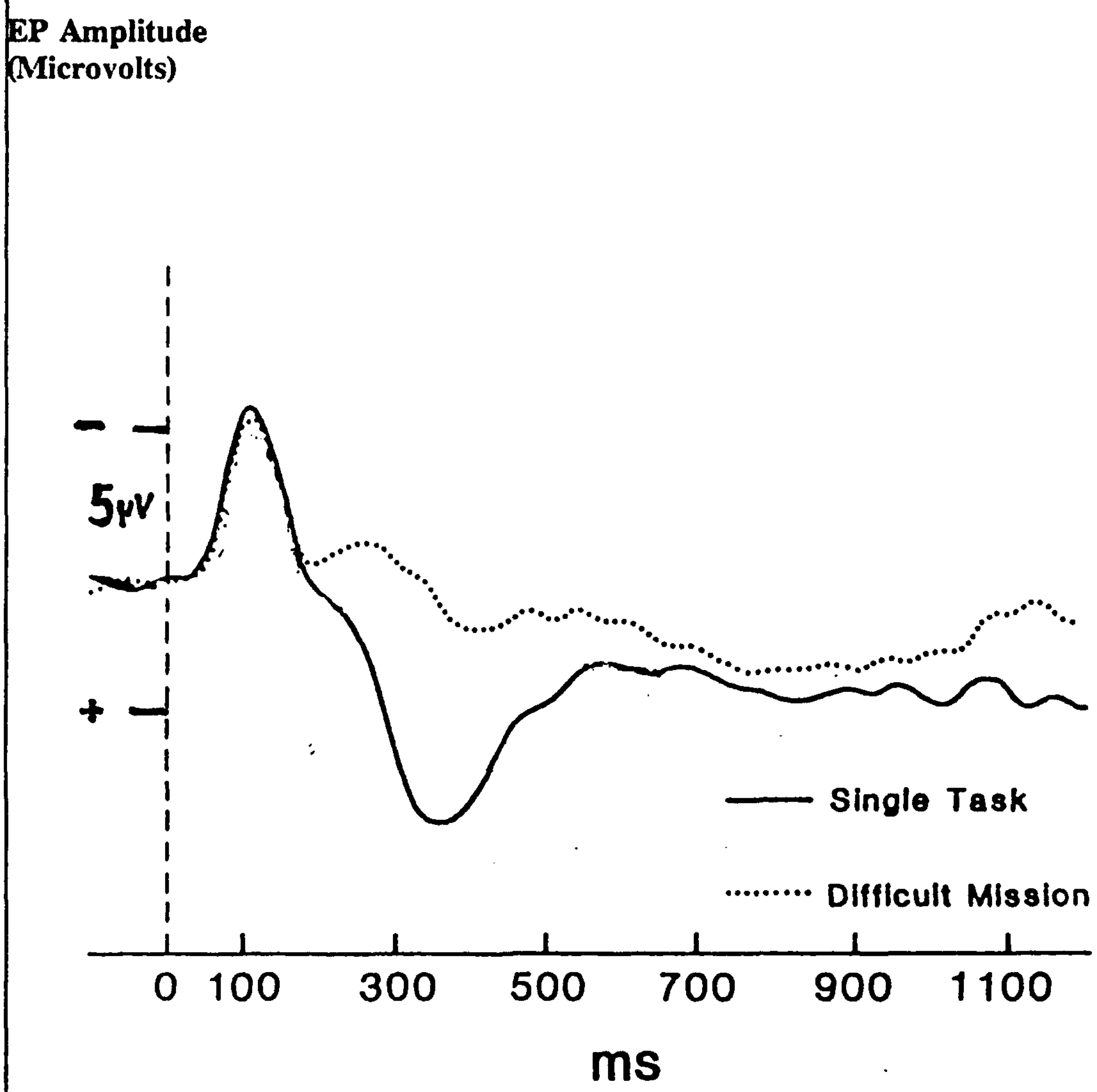
In 1983, Kramer, Wickens, and Donchin characterized P300 as a positive polarity voltage oscillation in response to a "task relevant, low probability event...whenever a person is required to update an internal model of the environment or task structure." This statement is based on the limited resource, single pool, mental model (Wickens) which postulates that the human has a limited source of mental potential and when tasked with multiple duties it will have to "work harder" to accomplish those tasks. In terms of the Wickens model, a change in voltage output will correlate to the addition of a second task which the experimenter controls. For example, during a primary task like tracking a moving point of light, a secondary task (a tonal signal) is introduced. This tone is either of a high or low frequency and, based on its frequency, the subject must recognize and acknowledge the proper tone. Concurrently, the subject is keeping a mental tally of the number of high or low tones and, consequently, when the appropriate tone is heard the subject must update their mental model and acknowledge the reception of the high or low tone. This mental model involves recognition of the proper signal and then acknowledgement of that signal by adding that tone to the mental tally of the times that they have heard that tone during the test period. The test scenario created by Kramer et al. involved this perception of the tone while the subject was performing a primary tracking task. The experimental variation was the difficulty of the tracking task.

Results of the Kramer, Wickens, and Donchin experiment showed that with increasing task difficulty there was a reduction in scalp voltage output (at the measuring site) recorded within a specific time after the tonal onset (Figure 5).

A significant problem area with the use of ERPs is the timing of the ERP signal tone in synchronization with a discrete aspect of the primary task. To overcome this issue, Wilson & McCloskey used a 250 ms delay from the presentation of the primary task to the presentation of the secondary tonal signal. In this way the subject was processing the primary task at the time the secondary tonal stimulus arrived. This resulted in amplitude changes which varied with task difficulty (Figure 5). Reductions in the amplitude at the P300 component are shown with increased levels of mathematical task difficulty in Figure 6.

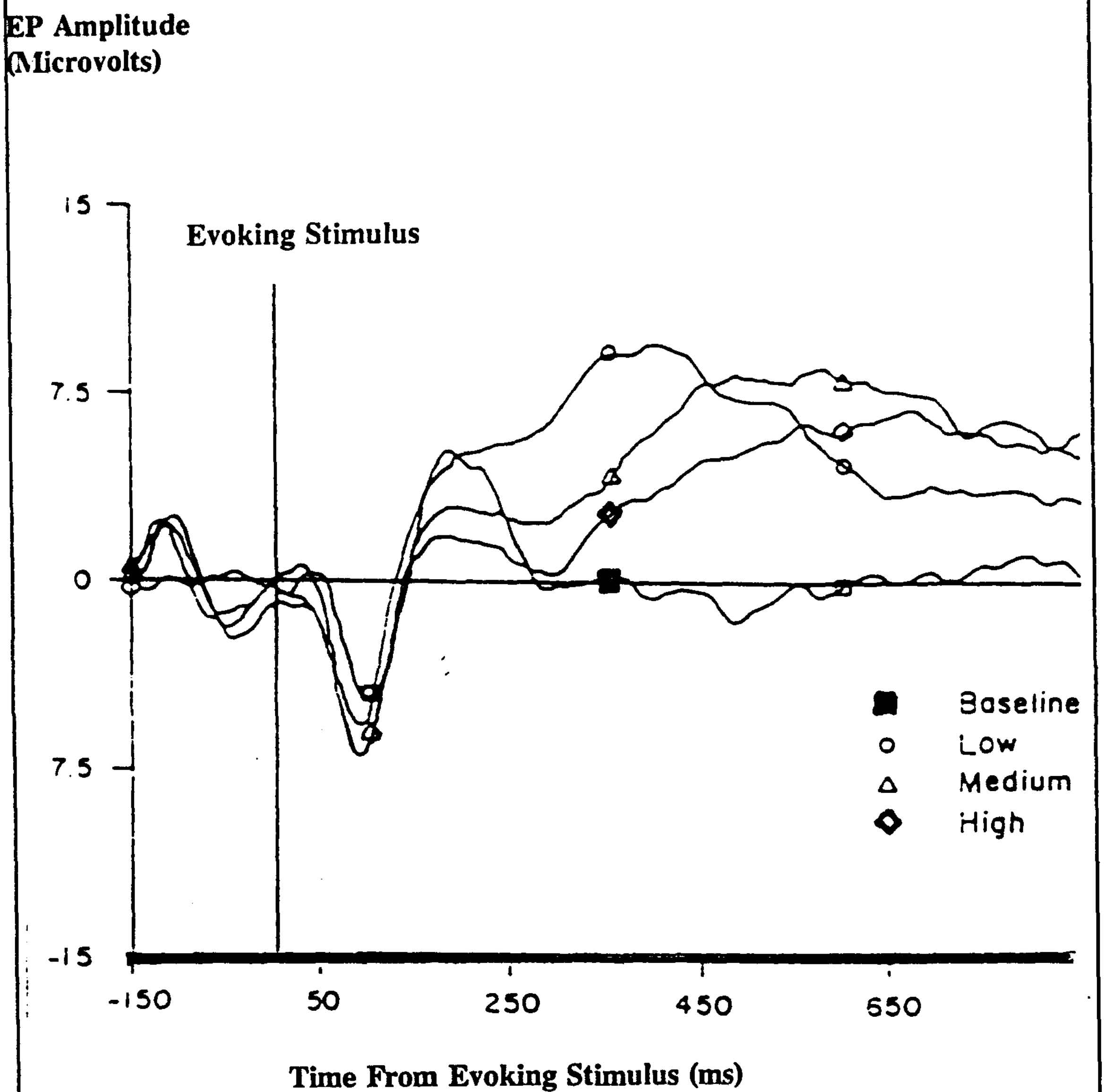
Wilson (1991) used different levels of task complexity with the Criterion Task Set (CTS) which was created by Shingledecker in 1984. The CTS is composed of cognitive tasks of varying degrees of difficulty and these were then introduced into the primary task. Figure 7 shows the ERP response from a midline parietal brain site (PZ) and its P300 component shows a reduction in amplitude with the two difficulty levels of a linguistic primary task.

The types of correlations associated with changes in P300 output are listed in Table 1. This table shows that the types of associations to various psychological phenomenon are extensive. That diversity of responses to an artificial stimulus over repeated trials yielding such a diverse psychological spectrum presents an interesting challenge for future research.



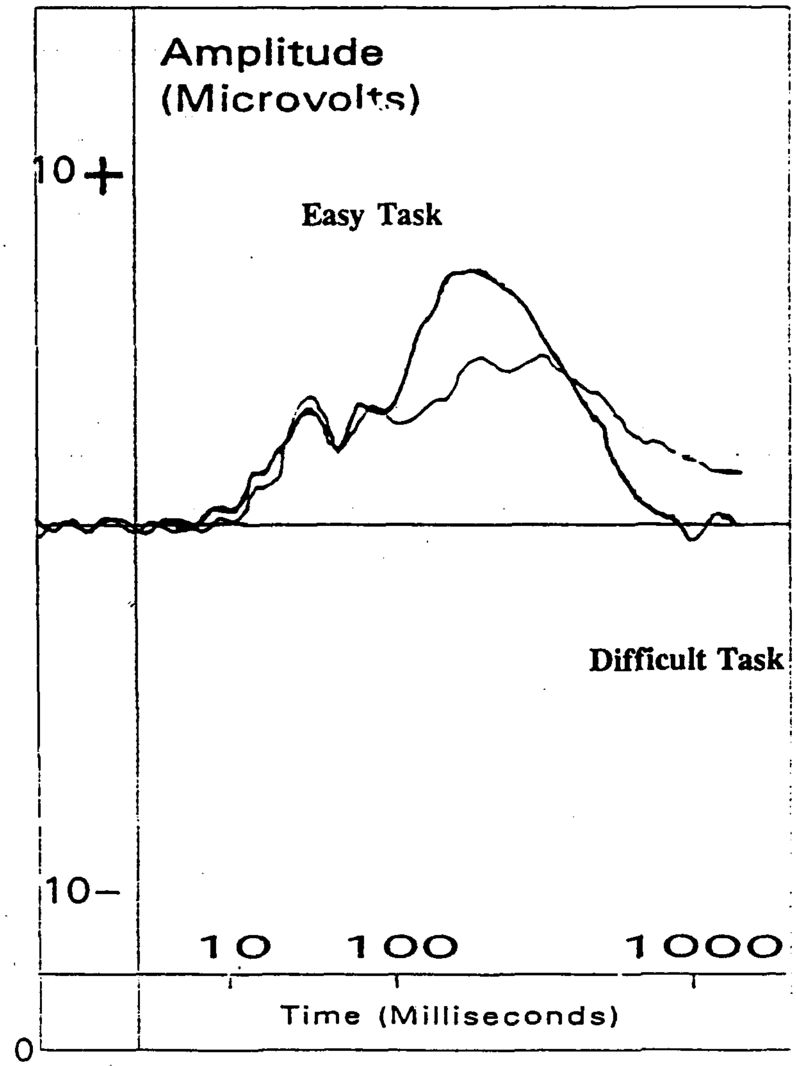
Changes in task difficulty and consequent workload increase are shown as reductions in amplitude values in the P300 range. (300 milliseconds after stimulus onset.)

Figure 5 EP Amplitude Reduction With Increased Workload



Evoked potential responses while performing a mathematics task of three levels of difficulty. Note reduction in amplitude in early components with more difficult tasks in the P300 range. Baseline value represents a tone response only condition.

Figure 6 EPs with Different Levels of Math Complexity



Two levels of a linguistic primary task taken from averaged Pz site data. Note reduced amplitude on the difficult task (second waveform shown). Total time is 1024 seconds of activity.

Figure 7 Averaged ERPs on a Linguistic Primary Task (PZ site)

Table 1.

ERP AND P300 ASSOCIATIONS TO PSYCHOLOGICAL PHENOMENA

Researchers	Year	Association with:
Sutton, Braren, Zubin, and John	1965	Uncertainty
Sutton, Tueting, Zubin, and John	1967	Information Delivery
Ritter, Vaughin, and Costa	1968	Orienting
Squires, Wickens, Squires, and Donchin	1976	Expectancy
Kutas, McCarthy, and Donchin	1977	Stimulus Evaluation
Ruchkin and Sutton	1978	Equivocation
Ruchkin and Sutton	1978	Value or Meaning
Donchin	1981 Context and Schema	Context and Schema Updating

The use of ERPs provides a classic psychological stimulus-response test paradigm, where a signal (tonal or visual) results in a response (amplitude fluctuation). Shortcomings to the use of this paradigm are due to the criticality of timing the ERP stimulus to the primary task, and also the possibility that ERP responses may be artificial in nature and overly intrusive to primary task performance. It is with these reservations that other forms of EEG analysis have been proposed.

Historical EEG Waveform Analyses

A vast array of EEG output has been measured from many cranial topographic locations. Where ERP measurements generally rely on a smaller number of electrodes, the use of spectrographic methods permits sampling the various EEG signals from many sites simultaneously. Using this enhanced array of sampling electrodes, an additional factor was usually included, which is segmentation of those signals into specific frequency and time bands. This methodology also used sampling periods of different lengths, called epochs. The selection of epoch lengths ranged from less than 1 second to minutes, depending on the researchers needs.

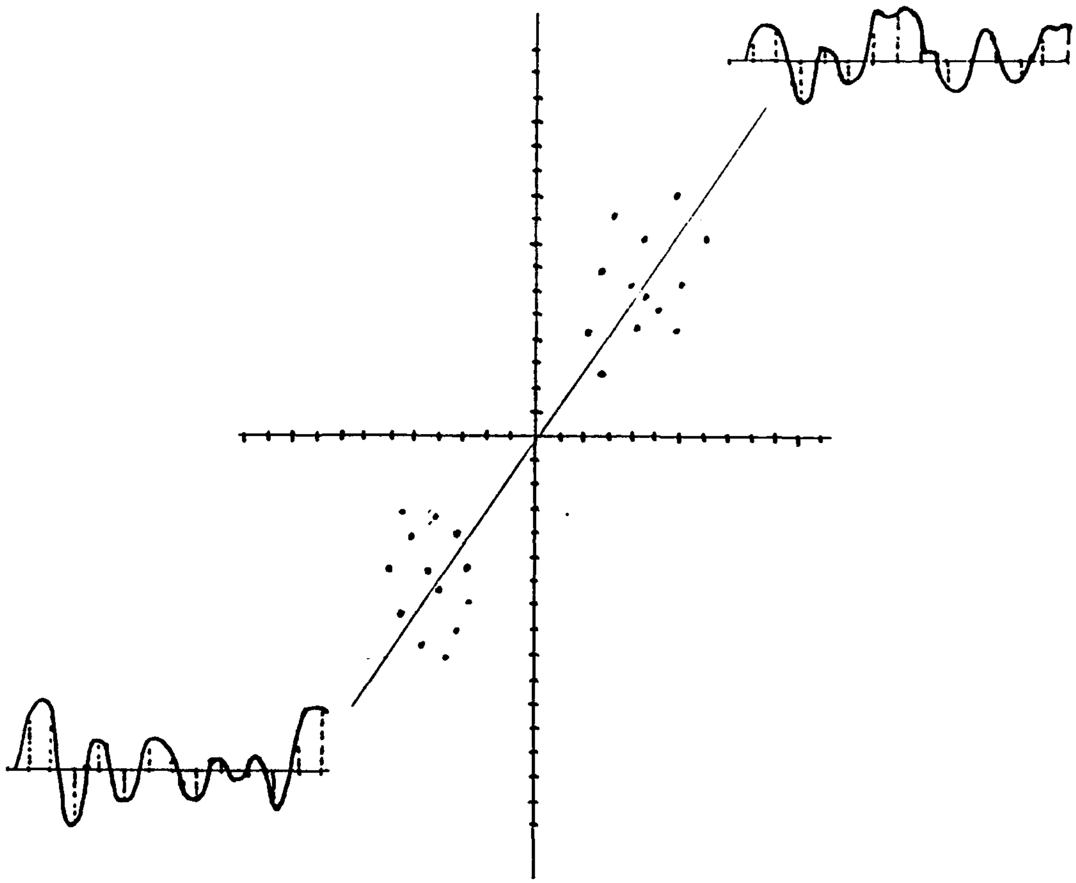
Early research in the area of spectrographic analysis used animals (primarily cats) as test subjects, and their EEG patterns were evaluated during sleep states. In 1967, a paper by Chase, Nakamura, Clemente, and Sterman discussed the concept of EEG alpha changes. An example of the development of the spectrographic technique is found in Sterman's 1981 study of the power spectral analysis of the EEG in humans, specifically epileptics. Spectrographic analysis gave the same information as ERP analysis but yielded a better understanding of site output without the use of intrusive "stimulus" signals. It could therefore monitor the continuous EEG output without the intrusion of external stimulus inputs on the primary task.

Analysis Methodology

There were numerous methods used to analyze EEG and ERP data, they ranged from visual inspection of waveforms to statistics and computer modeling. Data analysis methods listed below have been used on both types of EEG data and are reviewed as possible techniques for future EEG analysis.

Regression

A number of researchers have used regression analysis for waveform data and an example is given in Shaw, 1984. Figure 8 shows a simple scatter diagram produced by plotting successive amplitude values of two wave forms. Using this model the predictive ability of one waveform can be compared to the second, as well as comparisons of variance differences. Often this analysis could be used for tests of inter-hemispheric differences (asymmetry) and would use the variance or mean amplitude ratio from homotopic sites of the two hemispheres (see Beaumont, 1983). Using the regression coefficient (ratio of the correlated parts of the signals), and the residuals, the waveforms could be analysed in terms of their variance in regard to the accuracy of the regression equation's predictive ability.



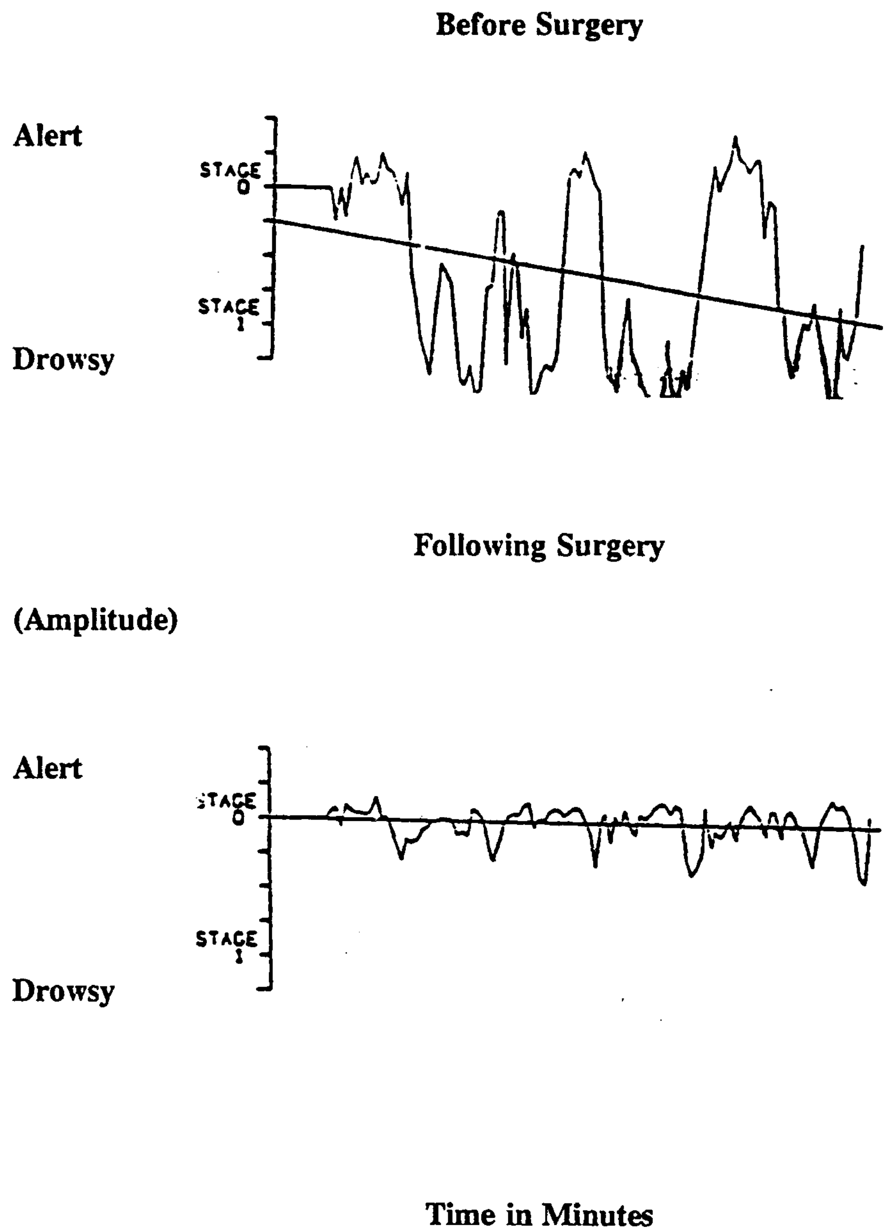
Amplitude values of two site waveforms converted into a scatter plot and fit with a least squares regression line.

Figure 8 Scatter Diagram and Regression Plotting

In terms of analysis, the study done by Matousek and Peterson (1982) on alertness functions used data from eight EEG sites in a regression model. The data in Figure 9 was from a patient with a hydrocephalus condition and was used in a multivariate model to assess surgical treatment effects on drowsiness. In Figure 9, a vigilance epoch period of 4 minutes was used to show decrements in vigilance as rated on a subjective scale of two sleep stages. These stages were from alert (stage 0) to drowsy (stage 1). A baseline level of alertness was begun at the horizontal line beginning at stage 0 and was caused by a flash of bright light to the subjects eyes. The data shown in this figure shows amplitudes plotted against sleep stages over a period of five minutes. Differences between the upper chart and the lower chart were due to the experimental treatment (surgery), and show greatly diminished power fluctuations. The specific power levels were not reported in this study, and therefore the graph is primarily illustrative of the technique of regression rather than serving to illustrate a specific hypothesis about frequency or power versus vigilance. What Figure 9 shows is that regression modeling has been used as an EEG analysis tool.

Another example of the use of regression modeling is from the AGARD Conference proceedings of 1988 (Electric and Magnetic Activity of the Central Nervous System: Research and Clinical Applications in Aerospace Medicine). In that publication, Sterman, Schummer, Dushenko, and Smith used a regression-based model to examine trends in performance in an enroute phase of a simulator flight task.

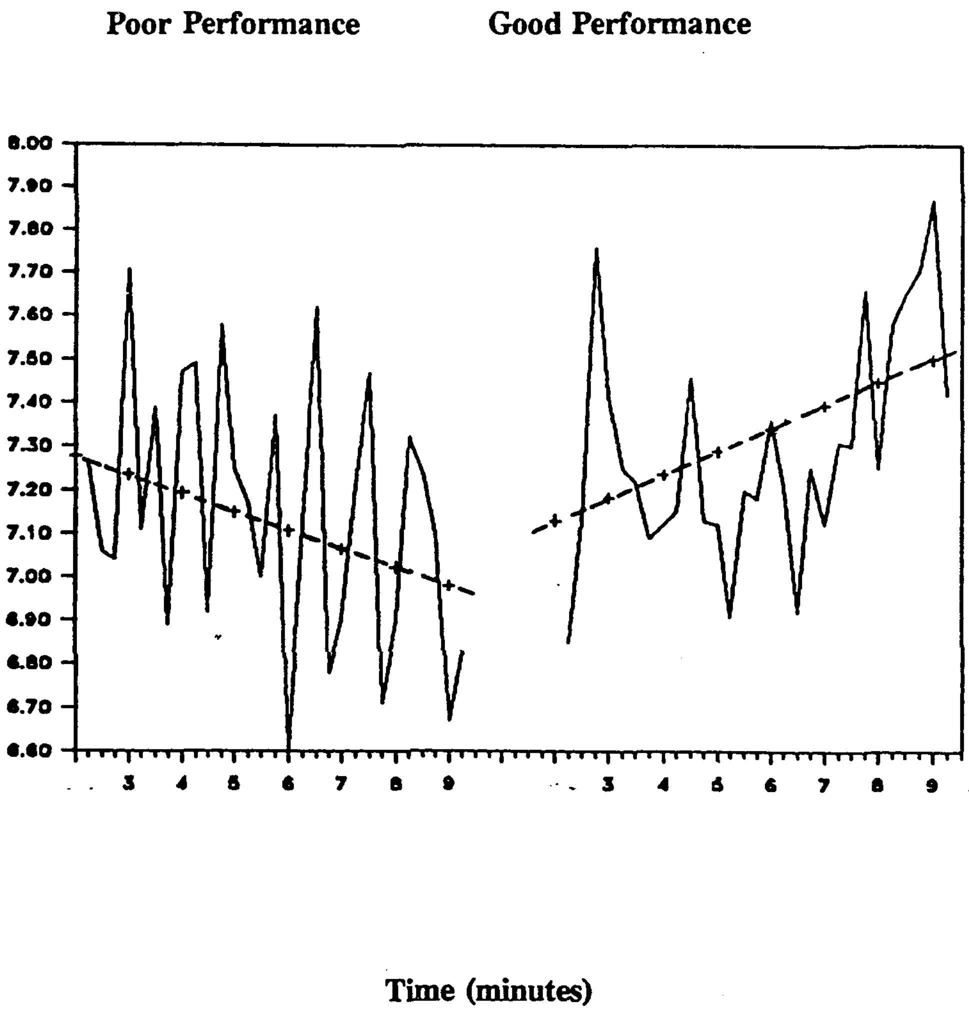
Figure 10 shows a comparison of modulation trends with task performance, modulation being defined as a variation in frequency or power. This is shown as a power spectral level versus time for poor and good task performance. Figure 10 shows that the slope of the regression line is decreasing with time in the poor performance category while it is increasing in the good performance catagory. This would imply that average power was decreasing over time with poor performance and increasing over time with good performance. Over the time of the test (10 minutes) there appears to be about a 0.25 to 0.30 microvolt difference between good and poor performance. It is not clear in this case whether the difference in microvolt amplitudes was statistically significant (no statistical tests of slope differences or mean microvolt amplitude were performed on this data). As an example of regression modeling, Figure 10 is illustrative of the concept, but not indicative of the predictive modeling capabilities of regression.
Assuming that the slope or amplitude values of the data were statistically significant, then the regression model could have had predictive power regarding mean microvolt amplitude or increasing/decreasing trends.



The upper model shows large swings from alert (stage 0 on the subjective scale), to drowsiness (Stage 1 on the subjective scale) over a period of 5 minutes. The amplitude values are not stated in the study but show dramatic reduction in the lower graph, due to the treatment effect (the treatment was surgery). A regression model fit to the data also shows corresponding trends by its coefficients (-0.59 pretreatment versus -0.10 post treatment)

Figure 9 Regression Modeling of EEG Signals versus Vigilance

Power Spectral Value (microvolts)



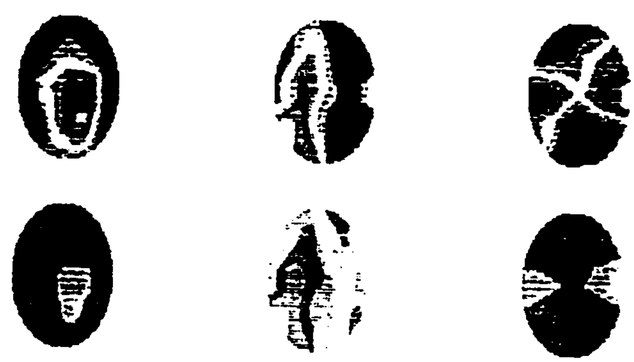
Comparison is made of the effect of good performance on a flight task to poor performance using discrete power spectral values (y axis) versus time on the x axis. Data are plotted amplitude values in the 8 to 12 Hertz bandwidth, and show increased periodicity in the poor performance task versus decreased periodicity with good performance. Also, note slope of the regression is different for both types of performance.

Figure 10 Regression Analysis of Power Spectra

Topographic EEG Analysis

Methods listed previously have looked at power trends by site or over different tasks without specifically looking at the location of those signals within the brain. Topographic analysis can look at power output within brain sites as an indicator of activity, and possibly workload. The analysis of this type of data is based on the anatomical purpose of each of the parts of the brain located under the 10/20 electrode site placement system. As a result of this anatomical knowledge an increase or decrease of electrical activity in a certain part of the brain, at a particular recording site, may indicate that a certain type of function is being performed. Examples of research involving topographic EEG interpretation are listed below.

Galin and Ornstein compared right and left hemisphere EEG signal asymmetry in their 1972 paper, which used power band records of right brain dominant vs left brain dominant tasks. Since that time computer aided technology had developed to the point where Sterman, and Suyenobu (1990) could produce brain maps showing activation areas by particular bandwidth. This capability is illustrated in Figure 11 which shows the mean power levels in an absolute (ABS) and relative (REL) scale over three different bandwidths. The use of the absolute scale is for between subject analysis while the use of the relative scale is for within subject analysis. The type of color mapping produced by this technology shows that at any one time there is greater or lesser activation of a site or combination of sites. Another advantage to this type of technology is the spreading activation of sites could concievably show the way in which the brain responds to different types of tasks or conditions. Figure 11 is illustrative of a qualitative analysis tool rather than a quantitative tool.



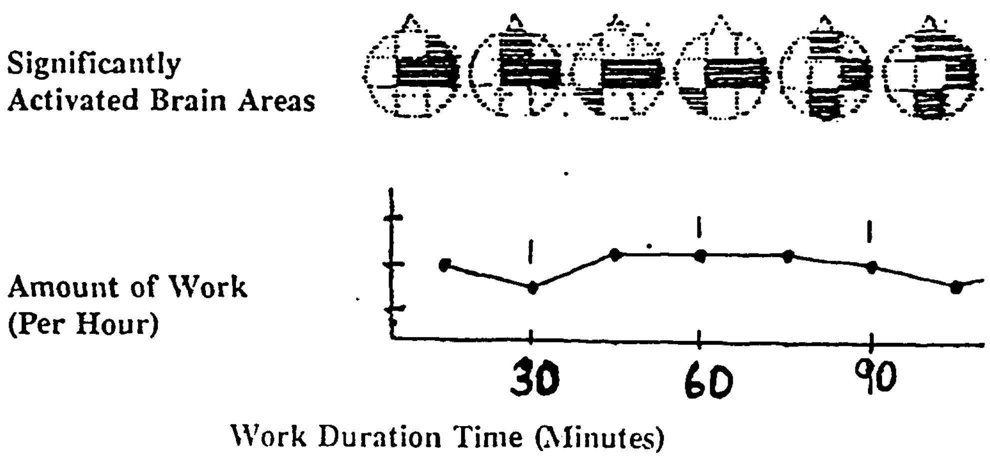
7.0 to 9.0 Hz. **9.0 to 11.0 Hz** **11.0 to 13 Hz**

Three bandwidth representations of brain activity shade coded using an absolute (top row)(between subject) value and a relative (bottom row)(within subject) value. Lighter color indicating greater activation.

Figure 11 Power Levels by Bandwidth

Topographic EEG technology is also shown in the study by Yamamoto and Matsuoka in 1990, where they studied VDT performance using frontal (f7, f3, fz, f4, f8) recording sites in the Theta (3.6 to 7.8 Hertz) band. Their article showed the significance of activation levels of the frontal area in terms of work speed and time on task. This is shown graphically in Figure 12, which was based on young adults, middle-aged subjects, and elderly subjects. In their study, the brain was segmented into nine areas on a geometric basis and those areas were classified regarding their output in the Theta Band (3.6 to 7.8 Hertz). Amplitude was classified into three catagories: mean + 2 SD (Standard Deviations), mean + SD, mean - SD, and mean -2 SD. This provided 3.5 microvolt steps with a maximum amplitude of 55 microvolts. Using a statistical approach like this provides a quantitative measurement of site activation, one which can be statistically tested for significance. As an example, Figure 12 shows the statistically significant changes in amplitude over time for all the sites measured. Once this information is correlated to the functions of those sites, the activation pattern may be related to the tasks being performed at discrete points in time. This provides a reliable method to track brain activation over time and should have far reaching consequences in examining activation potentials in regard to tasks which require a fairly long period of time to complete. This study was based on the quality and amount of VDT work produced by the time in minutes allowed.

The essence of Figure 12 is that the measurement of brain activation by site is an evolved technology. What must follow from this information is the ability to predict and correlate brain activity, in terms of activation, to the level of difficulty of tasks and workload conditions.



Locational (topographic change) over time with extended periods of work, shown by Standard deviation levels, representing amplitude from monitoring sites.

Figure 12 Standard Deviations of EEG Activation Over Time

Simple Signal Detection Methods

An early analytic method used by Yingling, in 1977, consisted of recording the polarity of signals from pairs of channels. This approach provided a simple, dichotomous selection routine which could quantitatively assess laterality, amplitude, and site interaction effects. Increasing complexity of hardware and signal collection provided more information than could be effectively manipulated using this method by hand. The next decade provided computer and measurement technology advances which allowed spectral analysis and topographic analysis to develop. Some of those methods will be reviewed with respect to their usefullness at the Flight Test Center's EEG work.

ANOVA and MANOVA

The use of Analysis of Variance (ANOVA) and Multivariate Analysis of Variance (MANOVA) have been used on EEG data from the early days of EEG measurement. The analysis of variance on power levels of ERPs have been used from the 1960's on and constitute the most prevalent form of quantitative assessment. The work of Donchin, Kramer, Wickens, Braun, Givens, and Wilson contains numerous examples of the use of these methods to assess EEG signals.

Spectral analysis with ANOVA was a prominent means for assessing EEG signals and is discussed by Gliner, Mihevic, and Horvath (1982). Electrode output was digitized at 128 samples per second according to the Nyquist sampling theorem of 1924. Conventional bandwidths of 0 to 3 Hertz; 4 to 7 Hertz; 8 to 13 Hz; 14 to 19 Hz and 20 to 32 Hertz were used and, for each trial a 10-second sample was examined for mean power and frequency. Mean frequency per bandwidth was determined by multiplying the intensity by the frequency per Hz unit in the bandwidth. This result was summed and then devided by the sum of the intensities. This created 10 second epochs that were visually scanned for artifacts and then subjected to a two-factor, repeated measures ANOVA. The dependent variables were energy or frequency in each bandwidth and independent variables were hemisphere by trials.

One of the problems associated with EEG data analysis and the use of ANOVA is the possiblity of probability (p) value inflation due to redundancy in the data. This redundancy may be due to overlap of one site to the next and to correct for this possible problem there have been procedures adapted to EEG analysis to compensate for this error possibility. Stanny, Reeves, Blackburn, and Banta point this out in their 1987 paper on naval aviator selection using ERP data. As an example, they obtained a p value of .000025 for a single test and then applied a Bonferroni correction to yield a conservatively corrected value of $p = .0018$. This value was arrived at by examining the effect that 72 correlations between hemispheric differences may have had in inflating the original probability estimate. Strictly speaking, the Bonferroni procedure is not a statistical cure for dependence in the data, it only compensates for the effect of variables which may create inflated p-value conditions. In this respect, the Greenhouse-Gieser correction or Huyhn-Feldt procedures are often used to conservatively correct the experimentally derived p value. Inflation of the p values in tests of this type may also be due to interdependence (nonorthogonal relationships) and may also result from hemispheric redundancy in terms of electrode site locations. Gilner, Mihevec, and Horvath also explored ANOVA interaction effects, since changes in hemisphere activation levels would be important. To verify the results of those interaction tests they used Post-Hoc comparisons with the Newman-Keuls procedure.

Correlation

This was perhaps the first method of analysis of EEG signals going back to the first EEG experiments. Comparisons of amplitude to work conditions have been used extensively since the early days of EEG measurement. Correlation analysis has been used since 1949 to measure correlations between site output and tasks in many aspects of brainwave research. Generally, a Pearson product moment is calculated on sucessive amplitude values which results in correlations as a function of time displacement. A correlation of this type is a measure of the strength of the association between two variables, where the strength of association is expressed as a linear relationship. The Pearson product moment is not sensitive to relationships which are not linear. Since these EEG data points are based on a traveling wave, the use of the Fast Fourier Transform (FFT) allows the computation to be calculated quickly. A disadvantage to the correlation function is that there may not be a correlation maximum at a meaningful value of lag. Use of coherence analysis reduces error from correlation with different lag periods. Coherence analysis uses the correlation between a pair of signals expressed as a function of frequency, but uses coherence coefficients, which are transforms of the correlation function.

Period Analysis

A method which has been used by Pigeau, Hoffmann, Purcell and Moffitt (1988) is period analysis. This method is based on the change of sign of the part of the waveform as it passes through zero which gives a measure of the waves "frequency." In addition, they calculate the power of the waveform by cumulative addition of the absolute voltage between zero cross events. In order to discriminate what they call "faster frequencies superimposed on the main waveform," they also applied a first derivative measure on the negative inflections in the EEG voltage and the time in between each of those events.

The location of the waveforms maxima and minima are equivalent to the zero crossings for the first derivative, but this analysis method may not be sensitive to lower frequency time segments. To counter this an algorithim is used which measures the time difference between minima and maxima, and associated with this time difference is a frequency measure. What this does is create a new "smoothed" curve. The drawback to this is that higher sampling rates are needed to compensate for the loss in resolution.

Historical EEG Analysis Summary

This discussion has reviewed several features of EEG measurement, Spectral Analysis, Topographic Analysis, and Statistical Analysis. Analysis of EEG for a variety of tasks have used these methods and it is expected that they may be used to assess workload in a flight test context. Quantification of workload in particular may be addressed using one or more of these techniques, and all have had a significant impact on EEG as a diagnostic tool in fields as diverse as detection of brain abnormalities to VDT usage. If there is a trend in the literature, however, it is away from the use of ERPs. It is proposed that the use of ERPs have less overall potential for flight test than spectrographic or topographic techniques. One of the reasons for this is that ERPs are more intrusive to the task at hand, as well as requiring multiple trials in order to be effective. The ERP may also be more suited to a laboratory environment rather than a dynamic flight test. In general, the use of ERP stimuli has been supplanted by allowing the task features themselves to determine critical points for assessment. If secondary tasks, or dual performance of tasks is required it can be woven directly into the task being performed and thus not create the intrusion of an extraneous signal such as may be caused by ERP stimuli.

Common EEG Measurement Hardware

Rather than proceed with a developmental, historical perspective, the following section will deal with primarily state-of-the-art EEG hardware which has developed over the past 10 years. Since this is a rapidly progressing field, the technology is constantly changing and it is through comparisons of several researchers that a clear picture emerges of what is being used in laboratories throughout the world. This section will also deal with some of the data processing assumptions which have been employed to date.

EEG Signal Detection and Measurement.

Electroencephalographic measurements are in the form of microvolts detected from the Thalamo-Cortical network. This structure produces gated discharges which are measured on the scalp at specific sites described by the 10/20 system. In early research, the metallic electrodes were usually gold or silver plated, and attached with collodion (a liquid plastic like material). This attachment is unacceptable for flight test for two reasons: (1) collodion is a viscous nitrocellulose suspension in a toxic, flammable, solvent mixture, and (2) when dry, the collodion tends to bond very well with the skin and may require flammable solvents for removal.

Currently, electrodes are cup type, lighter in weight, and are "attached" to the skin by use of a gellatinous, highly conductive paste. There are also "dry" electrodes which may be attached to areas of the body which are not heavily covered with hair.

The Air Force Flight Test Center, in cooperation with M.B. Sterman and his associates at the University of California, Los Angeles, have developed an electrode placement system adapted to flight test. Electrodes are held in place by a standard elastic skull cap equipped with portals for the electrodes. This skullcap has the portals situated in accordance with the international 10/20 system of placement. In the 10/20 system, the distance between the sellion (nasion, bridge of the nose) and the inon (bony protruberence at the back of the head) is divided into equal increments longitudinally and laterally. This provides an even spacing of electrode sites, see Figure 1. The strength of the EEG signal is also magnified by the use of sophisticated preamplifiers mounted inline at the electrode site.

Two examples of measuring and processing the EEG signal are included as examples of two current methodologies. The first is the procedure used by Gratton, Coles, Sirevaag, Eriksen, and Donchin (1988) for ERP measurement, the second is a brief description of the method used by Sterman, Kaiser, and Mann (1992) used for continuous EEG measurement. These descriptions include capturing the signal and processing the signal prior to analysis. The experiment described by Gratton also included the measurement of Electromyograms (EMG) and Electroculargrams (EOG).

Gratton's measurement of the EEG signal for ERPs was taken from Fz, Cz, Pz, C3, and C4 (see Figure 1 for locations), and was referenced to linked mastoids with Burden type Ag/AgCL electrodes. Impedance was less than 5K Ohms, and the signal was amplified by Grass model 7P122 amplifiers. That signal was filtered on-line with a high frequency cutoff at 35 Hertz and used a time constant of 8 seconds for the high pass filter. The voltages were digitized at 100 Hertz for 2,100 ms, and at 100 ms prior to a warning cue to the subject, and ended 1 second after the test array was presented. A correction was applied for vertical and horizontal ocular movement artifact using a modification of the procedure described in Gratton, Coles, and Donchin (1983). Their data were then smoothed using a low pass digital filter (high frequency cutoff at 3.1 Hertz, with two iterations). The signal baseline was averaged for the first ten points of the epoch (approximatly 100 ms) and that average subtracted from the total signal to yield the ERP waveform.

The next description is taken from Sterman, Kaiser, and Mann (1992)(In-Press). Using the 10/20 system, 19 recording sites were referenced to linked ears. Impedance was tested and found to be below 5K Ohms. Prior to the test the EEG recording system was calibrated using an MS-20 Miniscope oscilloscope (NonLinear Systems, Inc.) with a custom designed signal generator. Using a method developed in previous studies (Sterman, Schummer, Dushenko, and Smith, 1988) a calibration signal was used which consisted of a 3-minute, 9.5-Hertz sine wave of 50 microvolts peak-to-peak. During testing, a Neurosearch 24 EEG system digitized the analog EEG signal at 512 samples per second, with a 12-bit A/D converter, and these digital sequences were then subjected to a Blackman-Harris minimum 4-term window to eliminate discontinuities in the waveform (Harris, 1978). The signal was highpass filtered at 2 Hertz (rolloff at 12 db per octave) and low pass filtered at 16 Hertz (rolloff at 48 db per octave). The data were then Fast Fourier Transformed and stored as 4-second epochs with a frequency resolution of 0.25 Hertz and listed as spectral density files in five bands. Frequency bands stored were, 5 to 7, 7 to 9, 9 to 11, 11 to 13, and 13 to 15 Hertz. The bands were scanned for artifact, subjected to additional filtering and common mode rejection, which eliminated all epochs of data over two standard deviations above the highest artifact-free values for a frequency band, (this resulted in loss of approximately 10 percent of the total epoch data).

The data are then natural log transformed in accordance with the procedures used by Gasser, Bacher, and Mochs, (1982). For more information on transforms, windowing and smoothing functions see Appendix 1.

Signal Analysis

ERP Data Analysis

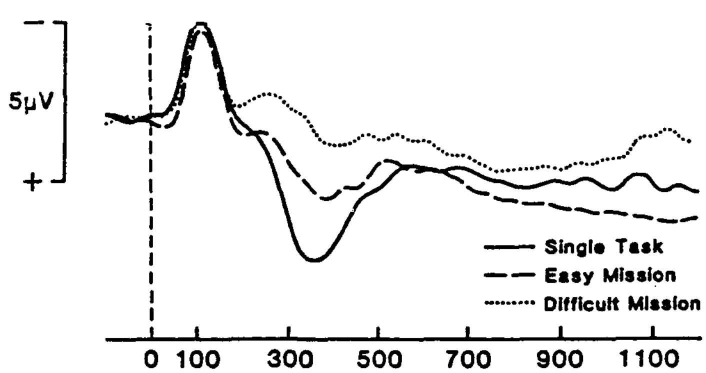
Figure 13 contains ERP wave representations resulting from three different levels of workload on a variety of flight missions studied by Kramer, Donchin, and Wickens (1987). Figure 13 plots the grand average ERP values (in microvolts) over 1,100 milliseconds. What this graph shows is a reduction in amplitude with increasing workload at the P300 temporal location. A tonal stimulus occurs at time zero and the ERP response develops into the characteristic pattern of large waveform deviations followed by a return to the steady-state EEG signal. The statistical analysis of that apparent difference is discussed in the following paragraphs. Two criteria overall were used to assess this ERP, amplitude and latency.

This data analysis was performed using both standard three-way and a repeated measures ANOVA. An example of this type of the three-way ANOVA included: for main effects, two mission types by two tone types by three electrodes. Analysis of Variance input used amplitude and latency of the P300 ERP. Results showed significant ($F(2,12) = 4.7$, $p. < .05$) main effects for differences in workload due to mission type as reflected by P300 amplitude. Post-hoc comparisons showed diminished P300 amplitude with increasing difficulty of the task. Latency data run through the ANOVA also showed significant ($F(3, 18) = 11.3$, $p < .01$) differences which the authors speculated reflected mission difficulty.

Kramer, Sirevaag, and Hughes in their 1987 paper on ERPs and performance discuss the analysis of ERPs, particularily N160, N190, and P300. For the negative components, both amplitude and latency measures were obtained by taking the average data from each electrode. These data were subjected to an algorithm which selected the most negative peak (relative to the mean prestimulus baseline in a latency window determined by visual inspection, and was 100 to 300 ms poststimulus). The analysis of the positive components for both amplitude and latency followed two different methods.

Amplitude variability was determined by using a covariance algorithim which computed the covariance using a cosinusoidal waveform within a moving 500-ms window. This window began 300 ms poststimulus and ended 800 ms poststimulus. The positive latency components were defined as the midpoint in the epoch which provided maximum covariance. A second method tried by Kramer on the P300 amplitude and latency, used a base-to-peak measure on single trials. His method analysed the largest positive peak in a 300 to 800 ms poststimulus window.

Another approach to ERP analysis involves a fusion of ERP methodology with Spectrographic methods and was used by Givens, Cutillo, Illes, Bressler, and Brickett. This is referred to as event-related covariance (ERC). This is performed using as many as 64 electrodes over 25 time intervals during a 4 to 6 second period from before stimulus to response feedback acceptance. In a typical test case, 50 to 100 trials are performed using 24 electrodes. Consistent event-related signals were averaged, filtered, and subjected to analysis. The analysis consisted of the signal magnitude and lag time of the sites sampled subjected to a covariance analysis. Each analysis compared all pairwise channel combinations to determine the effect size of the waveform distortion and its covariance with other sites. The significance of the ERCs was compared to the standard deviation of the noise signal.



Note reduced amplitude of P300 component following tasks or missions of varying complexity. Also note reversed scale of positive being plotted as a downward trend while negative is being plotted as an upward trend. Responses are Parietal grand averages for a tonal discimination task and two flight missions of two levels of difficulty.

Figure 13 Parietal Grand Average ERPs For Two Levels of Task Difficulty.

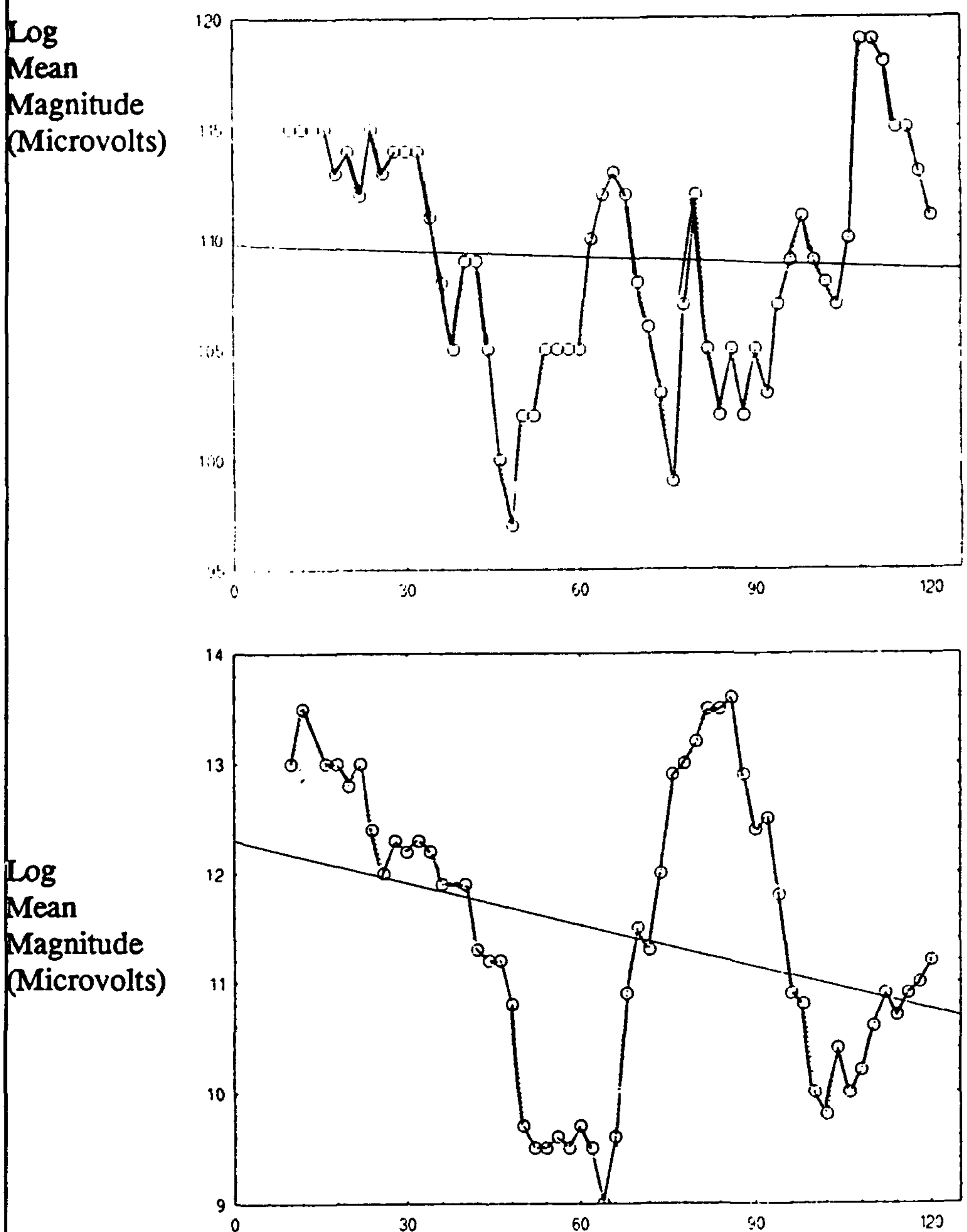
Current EEG Analysis Techniques used at the AFFTC

Analogous to the use of ERPs to study a variety of mental processes, the use of the overall EEG signal from multiple site electrodes provides greatly enhanced data collection opportunities and challenges. Using from 12 to 64 electrodes, gathering data at 128 samples per second over periods of time exceeding 12 hours, and viewing this data through the window of FFTs in four or more bandwidths provides a vast amount of data which must be converted to information. Much of the early "data analysis" for EEG was simply visual scans of EEG printouts. Indeed much of the current EEG "data analysis" consists of visual scans of xy plots, regression lines, or topographic spectral "landscapes." The reason for this is clear, the complexity of the data presentation does not allow for simple statisical hypothesis formulation and test. What follows are several investigator's attempts to quantitatively analyze such data.

Regression Modeling

An example of the use of a regression model was previously shown in Figure 9. However, Figure 14 shows regression modeling applied to a single site, single bandwidth test. Figure 14 represents a low workload vs high workload situation using log mean magnitude (in microvolts) versus task time in seconds (0 to 120). Figure 14 is based on an EEG flight test accomplished by the AFFTC Test Pilot School in April 1992, and recorded by Sterman, Mann, and Kaiser of the University of California, Los Angeles. The experimental variable in this study was the degree of handling control available in an NT-33 jet trainer. Four pilots flew a set course using three types of handling qualities control "programs" for the aircraft. The mission flown was representative of normal flight manuvers and included banked turns, takeoffs, landings and routine flight procedures. What Figure 12 shows is that for a single site, and on a given flight procedure, a pilot had a good handling qualities program for the low workload condition and a poor handling qualities program for the high workload condition. The designation of good versus poor handling qualities was subjectively determined based on a group of the NT-33 Aircraft contractor personel (Calspan Corp.) and USAF test pilot's opinions over an extended time period. The ratings of the handling qualities programs were not revealed to the test pilots during this experiment other than they knew there would be better and worse types of handling qualities control programs available for each flight.

Much of the data analysis methodology used in the TPS study was organized by Hunn, in 1992, and is reviewed in the following pages. Figure 15 shows a single site (F3) output in the 8 to 12 Hertz bandwidth for a test pilot subject. The log mean microvolt values are shown subjected to a 20 second smoothing function proposed by the UCLA team. One hypothesis for this test was whether the data from one or more sites could be correlated



Note change in periodicity from high workload (upper graph) to low workload (lower graph). Y axis data are log mean magnitude, x axis data are time in seconds, with a 2 second epoch length, all from F3 site. Also note the change in amplitude trend with high workload to low workload conditions. Frequency range is 8 to 12 Hertz.

Figure 14 Regression Model (High Versus Low Workload), P3 Site.

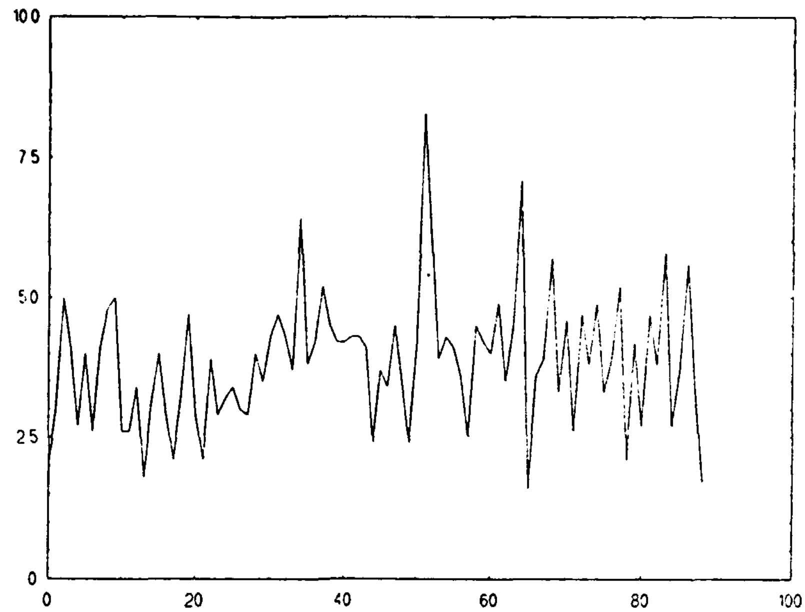
with different levels of mental workload based on Alpha band (8 to 12 Hertz) supression. This question is addressed by the waveform pattern shown in Figure 15. This data analysis used a 20-second smoothing function which creates a large peak-to-peak distance in the low workload data vs the high workload data. According to M.B Sterman, this trend is consistent with Alpha supression.

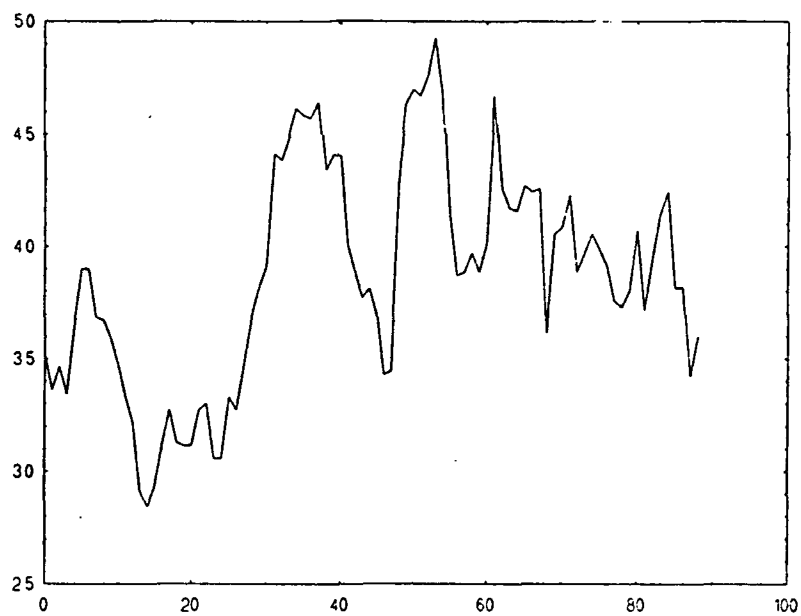
Based on research in a variety of settings, it has been demonstrated that when placed under varying degrees of task loading, the human brain modifies its alpha band emissions. Causation, or even strong correlation for this effect, has not been demonstrated definitively, but its occurance has been reported in numerous studies. It is important to note that in terms of data analysis any such attempt to demonstrate Alpha supression would be dependent on the proper degree of smoothing function applied. The epoch length would also be critical in determining the degree of precision with which a decision could be made regarding waveform output for a discrete event. In this case, the use of a 20-second smooth rate was not correlated to discrete performance events.

Various smoothing functions are often applied to EEG data by varying the grouped averaging of the data, i.e., the period of time which constitutes an individual epoch or a smoothing average length, the resultant waveform will change shape dramatically. Selective management of the length of the waveform timeframe may allow the researcher to see patterns of activation which may not be obvious in the FFT or raw data. There is also a significant risk of creating patterns where there are no obvious connections to performance or task difficulty. Examples of wave form smoothing are shown in Figure 16. This figure shows the potential for error when using a smoothing function while assessing a discrete point in time. An arbitrary zero line is superimposed on the three graphs which have an original signal, the same data with a 7-segment smooth, and the original data with a 21-segment smooth. The segments in this figure are based on a 2 second epoch length. The potential for error is possible not only in creating a trend over time which may lead to erroneous conclusions about task performance, but more importantly may lead to a considerable error when examining discrete events. In the case of discrete events, the superimposed line would reveal that microvolt output was rising in the first graph, had reached a negative low point in the second graph, and had reached a peak in the third graph. The implications for this are clear, the use of smoothing functions must be used with caution, particularily with interpretation of discrete events.

Waveform Amplitude Measures

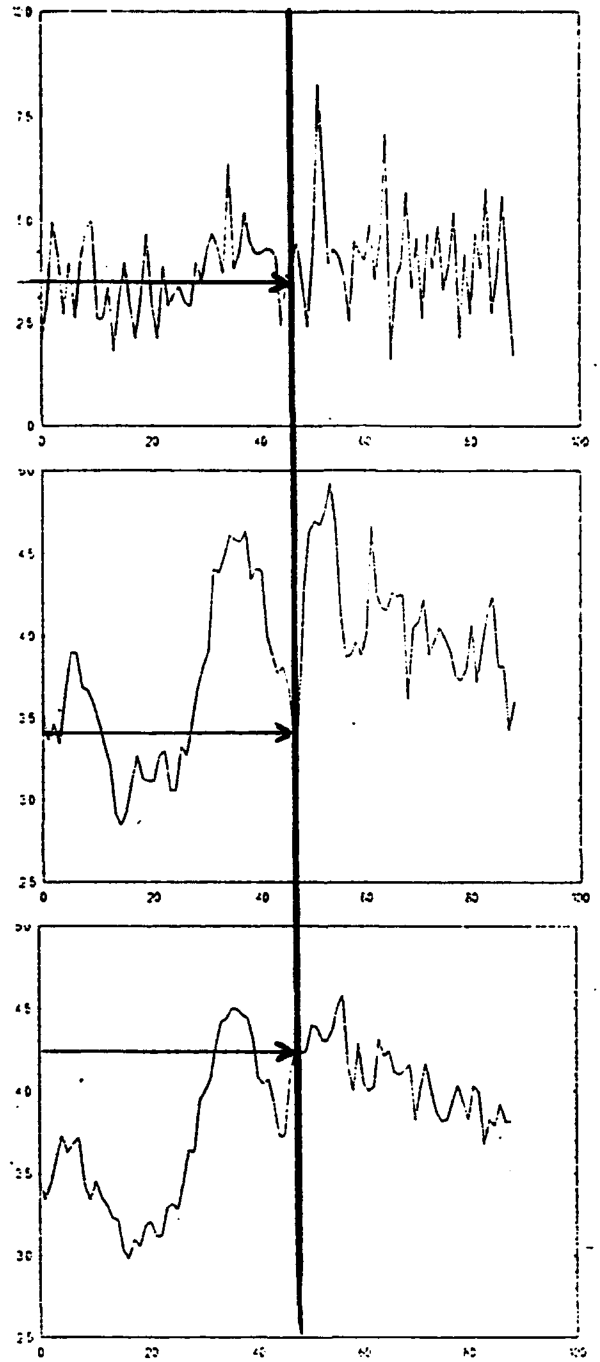
Amplitude values of the single site Alpha band were also examined for the data in Figure 14 and they show a pattern of alpha amplitude reduction with a log mean value of 1.4 microvolts in the low workload condition to a log mean of 1.09 microvolts in the high workload condition. The significance of this difference was not statistically tested.





Comparison of an orignial waveform (upper graph) and the same waveform subjected to a 7 segment smoothing function (lower graph).

Figure 15 A Smoothed Waveform



Comparison of a discrete point in time (shown by the vertical line) using the same data in its original form (top graph), with a 7 segment smoothing function (middle graph) and a 20 segment smoothing function (lower graph). Note the different conclusions which could be drawn regarding amplitude or polarity of the signal at a discrete event time.

Figure 16 Effects of Smoothing Windows on Discrete Event Interpretation

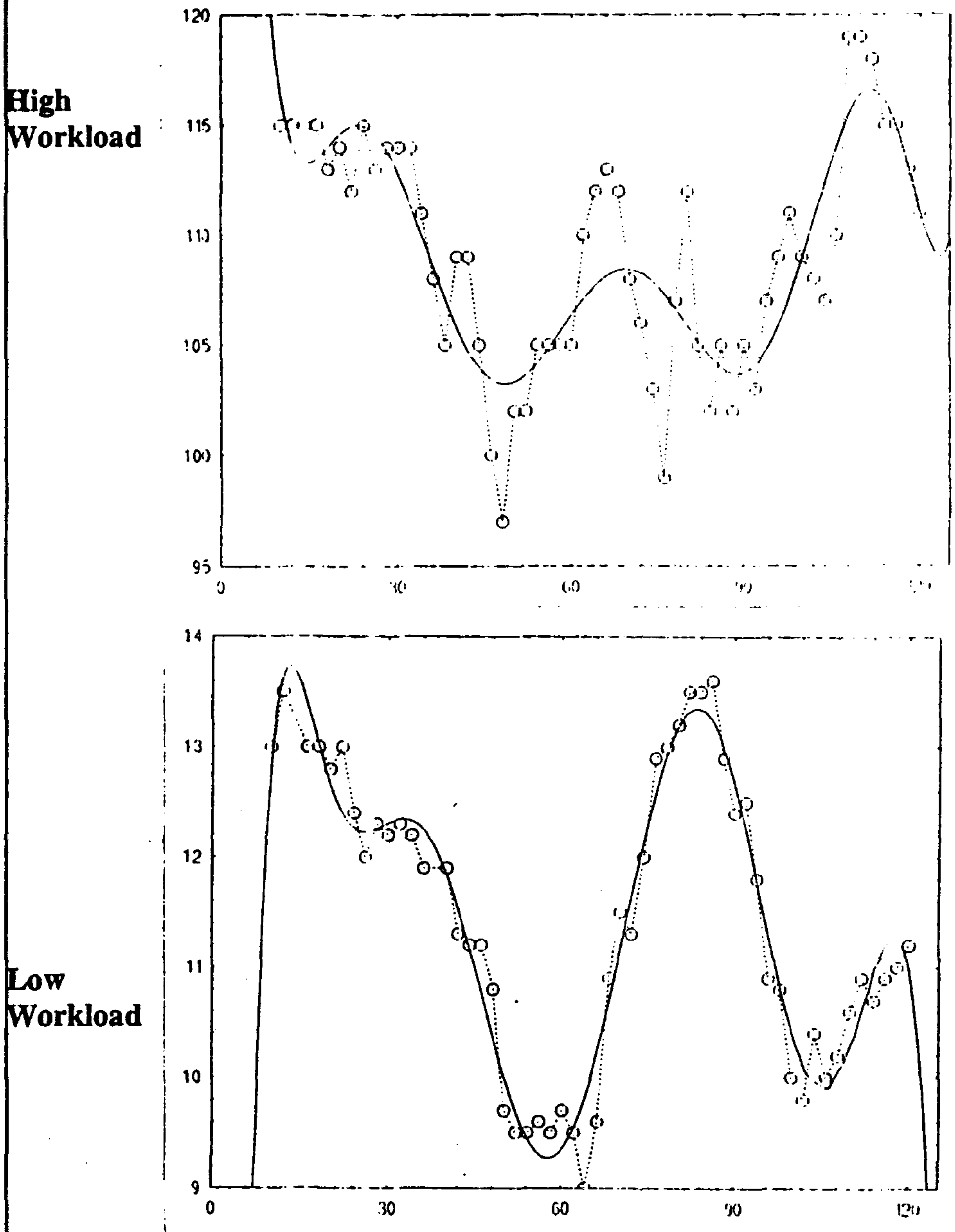
A second variation of amplitude analysis (Hunn, 1992) used the integral of each of two waveforms associated with two levels of difficulty of a flight related task. On the two different tasks, taken with one subject, an integral value of 126 microvolts was derived for a low workload task versus a value of 120 microvolts for a high workload task. The integral was chosen to add a slightly different focus to the technique of using a mean amplitude as an overall index of activation, in terms of overall power expended on the task. Comparison of the integrals of the two curves would only have application in a within subjects comparison, with all matching variables held constant. It would be very inappropriate for between subject comparisons due to very large differences in individual brainwave processing. The use of the integral of the waveform has not been tested as a predictive indicator at this time; its use has been postulated as a possible analysis tool for within subject comparisons. It is speculated that the mean or integral value of the waveform may have less predictive potential than waveforms shape. Observation of several data sets under different conditions indicates that the periodicity of the waveform may have a higher correlation to task difficulty than amplitude measures.

Polynomial Waveform Modeling

Several approaches were tested at the AFFTC by Hunn (1992) regarding the possibility of modeling the EEG signal from a single site using a polynomial model. Incremental steps were taken to accomplish this process by using lower order polynomial approximations which gave increasingly more accurate approximations to the waveform. The final attempt to model this waveform used a ninth-order polynomial approximation (Figure 17). This wave approximation was computer generated using EASYPLOT TM, however, a mathematical model with this degree of complexity could not plot the EEG signal in the high workload condition with an accurate degree of representation. It is postulated by Hunn that the failure of the ninth-order polynomial modeling would not preclude the use of still higher order polynomials, however, powerful computing facilities would be critical to that effort.

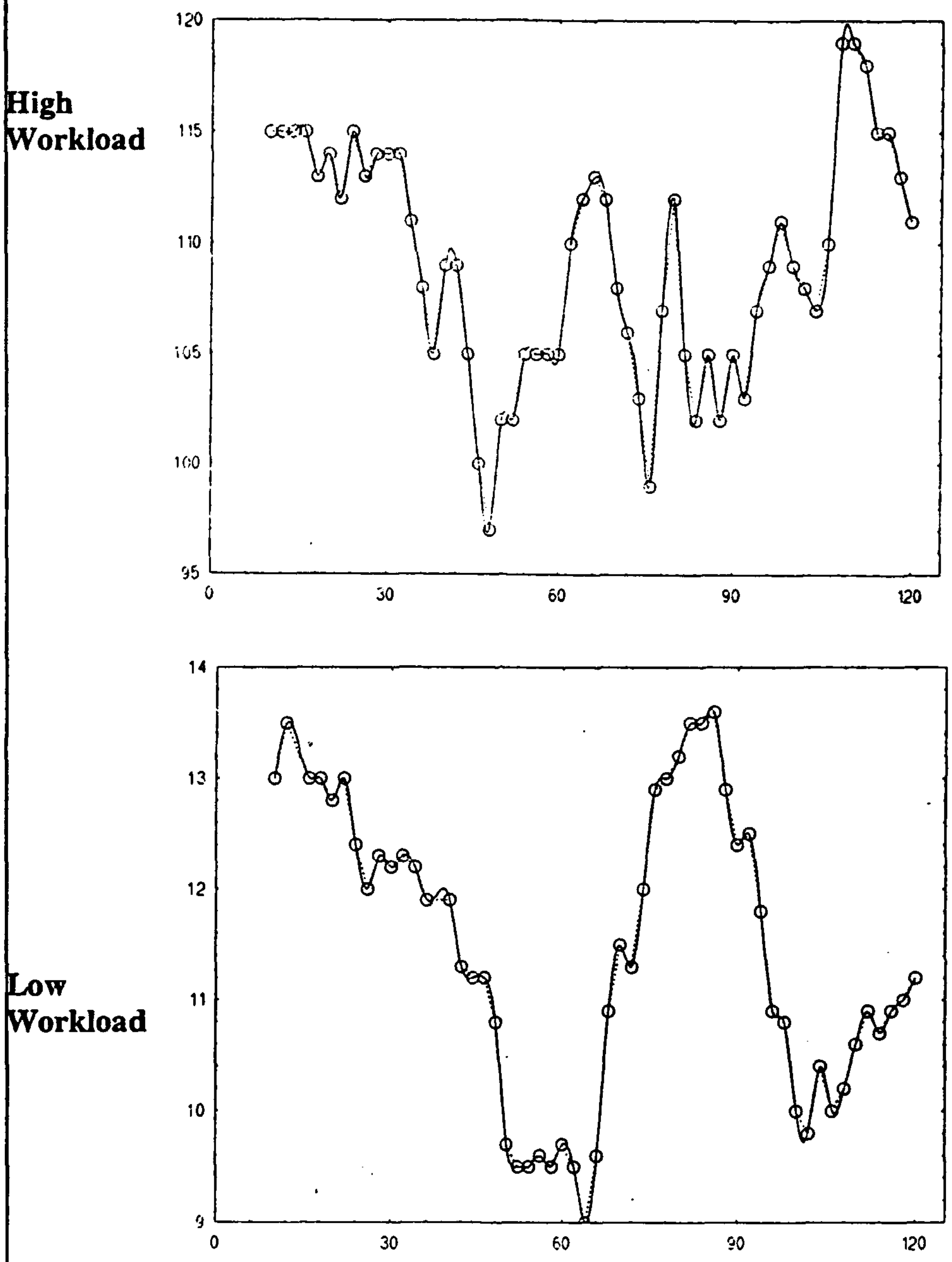
Cubic Spline Waveform Modeling

To deal with the inadequacy of lower ninth order polynomial approximations a second graphic representation of the EEG waveform data was created using a cubic spline model (Figure 18), which provided a much better fit to the data. This method calculates a waveform which passes through every data point and has continuous first (slope) and second (curvature) derivatives. It is based on third order polynomials placed together to match slopes and curvatures. It is a "natural cubic spline" because the end curvature is set to zero. Figure 18 shows that this can easily replicate the curvature of the high and low EEG waveform. It is felt that this computer-generated (Easy Plot, TM) graphic tool may have significant potential in modeling waveform activity, in terms of its geometric analysis potential. Sections of any waveform can be plotted and analysed using this technique and if waveform geometry can be used as a correlate to discrete events, then



Note ninth order polynomial fit to high workload (upper graph) versus low workload (lower chart). Discarding the tails of the polynomial, note the degree of fidelity of this model with low workload and the lack of fidelity with the high workload model. Data are log mean microvolts (y axis) by time (x axis) in seconds.

Figure 17 Ninth Order Polynomial Waveform Modeling High and Low Workload, P3, 8 to 12 Hertz



Cubic spline modeling of high workload (upper graph) versus low workload (lower graph). Log mean microvolts (y axis) versus time in seconds (x axis).

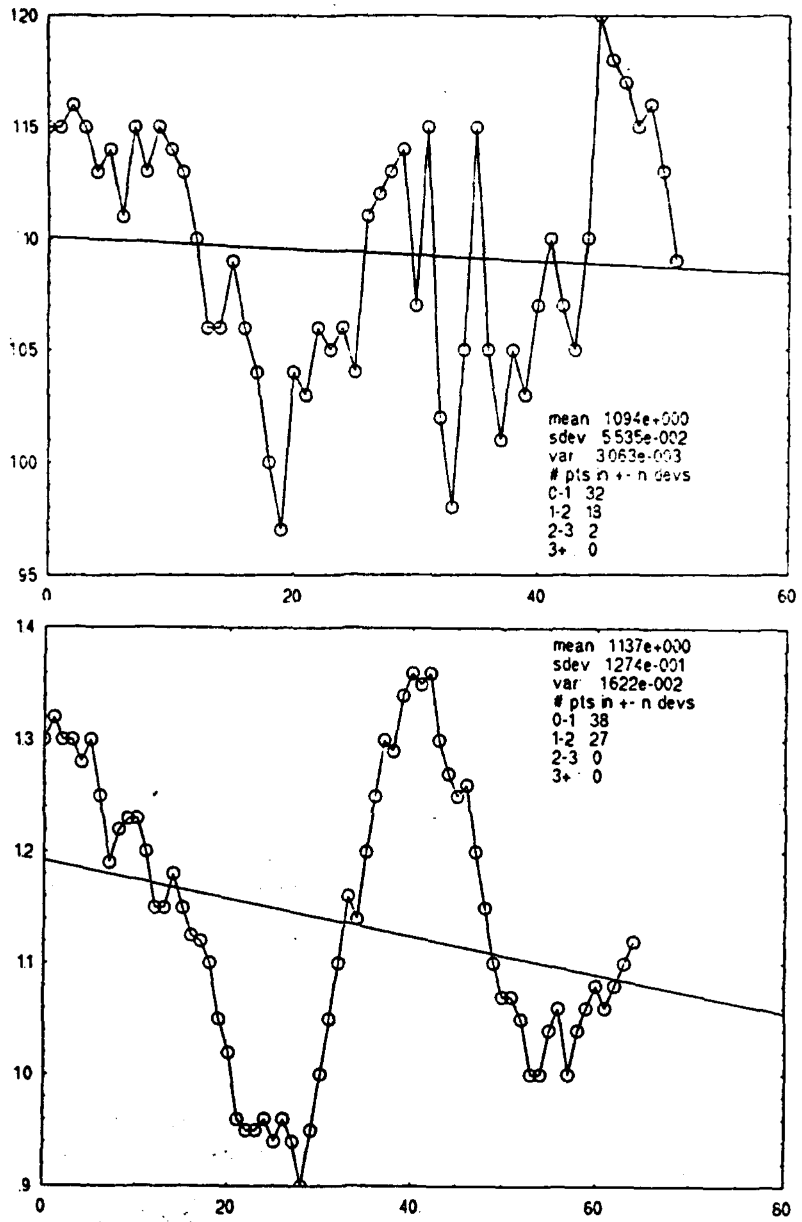
Figure 18 Cubic Spline Waveform Modeling High and Low Workload, P3, 8 to 12 Hertz

this technique can be very useful in determining workload and EEG associations.

Waveform Standard Deviation Distribution Plotting

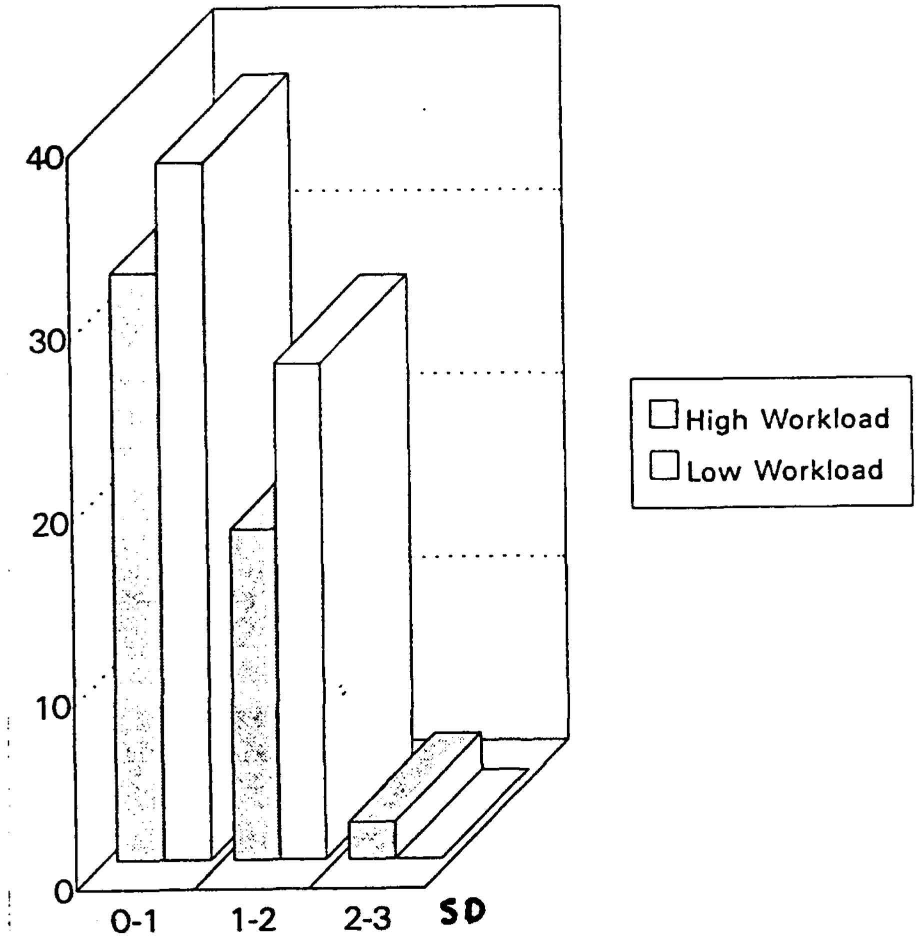
The last analysis (tested by Hunn, 1992) used the variance of the waveform in terms of catagorical levels of standard deviations, see Figure 19. This use of variance measures to compare amplitude and waveform parameters provided the most adaptive tools used in the AFFTC study. The example in Figure 19 shows the output by standard deviation classification bands which may then be graphed (Figure 20), or be subjected to further regression or advanced statistical analysis such as cumulative distribution function (CDF) analysis (see Bachen, 1988). Data of this type can provide an assessment of waveform in terms of its periodicity rather than a mean amplitude measurement.

Figure 19 shows a high workload situation waveform and a low workload situation waveform taken from the same subject. The deviations from a regression model are shown in that figure as frequencies of standard deviations by groups. For example, the high workload case has 37 examples of standard deviations in the range of 0 to 1 standard deviations, while the low workload case has only 29 examples of standard deviations in the 0 to 1 standard deviation catagory. Considering the distribution of the frequency of these standard deviations, by category, Figure 20 then plots those distributions comparatively. Figure 20 shows that in the high workload condition the frequency of the standard deviations is distributed almost normally, while in the low workload condition there is a trend toward greater numbers of deviations in the range of 0 to 1 and 1 to 2 standard deviation range. This would indicate that in terms of periodicity the high workload condition is characterized by a lot of abrupt, shorter deviations, while in the low workload condition the trend is toward the range of 1 to 2 standard deviation "excursions" from the regression line. Since this data was taken from the 8 to 12 Hertz band, there may be supposition that it reflects alpha supression in terms of the periodicity of the wave as measured by standard deviation groupings. At this time there is not enough supporting evidence to confirm that supposition, the technique is merely illustrated as a potential evaluation tool.



High workload (upper graph) versus low workload (lower graph). Log mean microvolts by time in seconds (2-second epochs). Deviations from the regression mean are recorded in the four catagories; 0 to 1 Standard Deviations, 1 to 2, 2 to 3 and 3+.

Figure 19 Waveforms and Tabulated Standard Deviation Frequencies (High Versus Low Workload Conditions)



Plotting the standard deviation distributions of these two conditions gives the opportunity to use a statistical measure as an index of periodicity. In the case of high versus low workload the difference is shown as high workload having a roughly normal distribution of standard deviations while low workload has a distribution which trends toward the 0-2 SD range.

Figure 20 Graphs of the Standard Deviation Distributions (High versus Low Workload Conditions)

Proposed additional analysis of this type of variance data could include comparisons of the distributions of the two workload conditions to develop predictive modeling correlations for individual performance. Statistical verification of these methodologies was not accomplished in the TPS study, due to lack of experimental design controls on the test, however, the techniques used will provide enhanced analysis capabilities for future studies.

It is important to note that the proposed analysis techniques and data reduction methods previously discussed are not an exhaustive listing. In particular, the use of single-site analysis and long-period smoothing are not recommended for immediate future study. The complex nature of the EEG signal demands a rigorous analysis procedure and long-period smoothing and single-site study may not be the most appropriate for the immediate needs of the AFFTC. Further examples of the complexity of EEG data analysis may be noted in the following paragraphs.

Spectrographic/Topographic Analysis Challenge Areas

The previous discussions of analysis methods bypassed a large number of applied technical questions which arise from this type of experiment. These areas include hardware problems and signal analysis complexity (including interpretation).

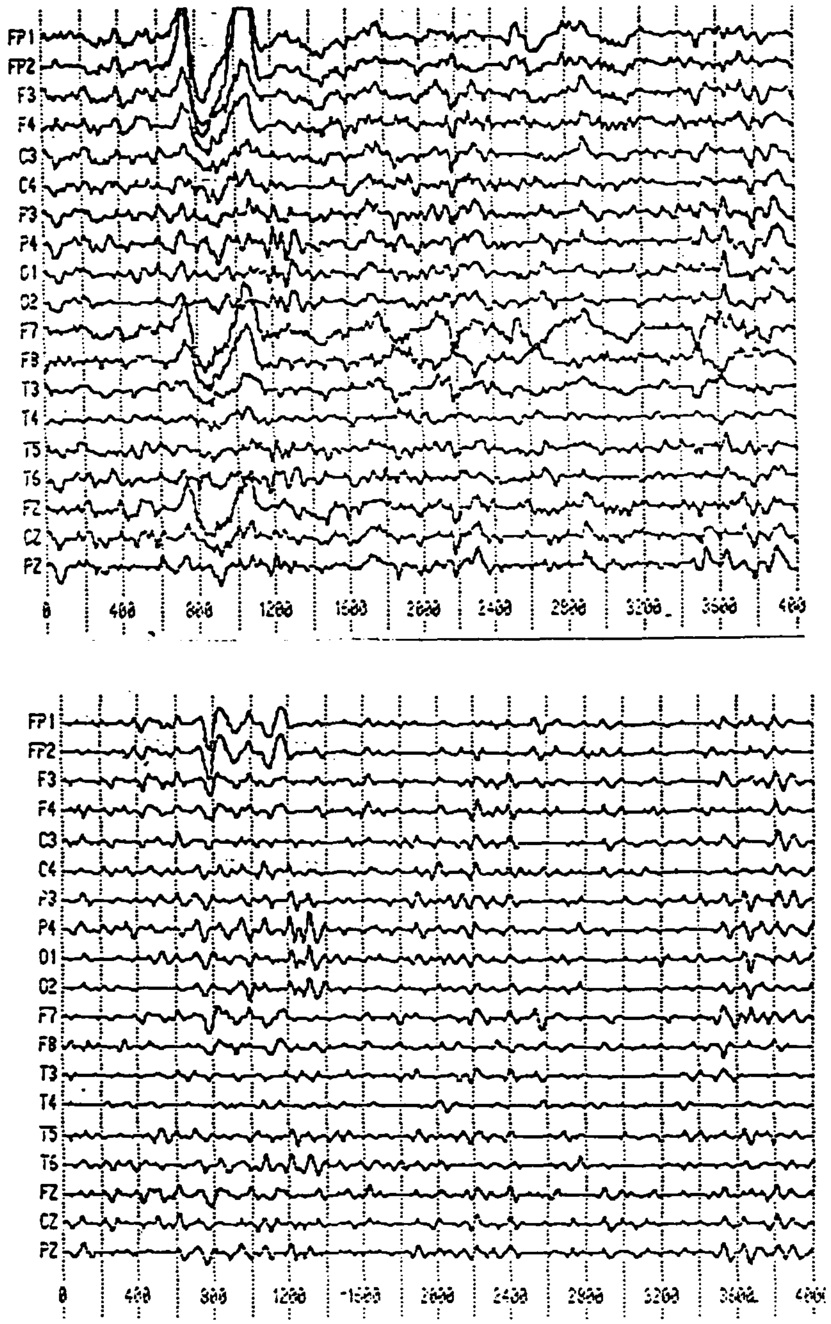
Hardware and Signal Collection

Typical EEG output is in the range of 0 to 20 microvolts and the non-evoked (endogenous) components are at the lower end of that range. Considering the low level of power being measured there is considerable possibility of electrical artifacts in the signal. At times it may not be clear exactly what is being measured in a dynamic task environment. For example, how are endogenous components isolated from exogenous components in a non-ERP test scenario?

Cognitive reactions to "extraneous stimuli" will produce the same effect as a planned evoked stimulus. Extraneous stimuli can be controlled in a laboratory environment but in a flight test scenario there can never be a true control from visual, audio, and somatosensory "extraneous" inputs. A flash of reflected sunlight, an unexpected radio squawk, or a turbulent air pocket will produce ERP responses identical to laboratory introduced stimuli. This does not imply that the response to those stimuli cannot be examined, however, from an experimental design point of view the lack of precise control over those stimuli becomes problematic. This is one of many reasons why ERP use has not gained widespread acceptance in a flight test environment.

The use of an ongoing signal, such as found in continuous EEG monitoring, has no assumptions concerning the particular timing of an event, however, it is critical that all behavioral events are closely time correlated to the EEG signal. Time correlation provides the connection from stimulus to mental processes then to behavioral actions. Another connection which is necessary is that of a record being made of the subject while performing the task. Two procedures have been used sucessfully to accomplish this task, the use of eye tracking equipment and video documentation. Eye tracking, when properly calibrated, can show the area that the subject is focusing attention in or out of the cockpit. It can provide a fair degree of precision in an environment which is not too dynamic, and is ideal for simulator use where the external variables of G load and safety of flight dynamics are of no concern. The use of standard video documentation, either head-mounted or frontal-body shots, also provide a bigger view literally and figuratively of what the pilot is doing or experiencing. This is particularily important from a kinesthetic sense, i.e., tracking control input movements and artifact creating muscle movements. The creation of muscle signal output by itself may even have diagnostic value for workload, but when it intrudes on the EEG signal then it becomes an unwanted artifact.

Artifacts are considered extraneous electrical signals from any source which create wave perturbations that may mimic or obscure the desired EEG signal. These can be caused by muscle movement, i.e., eye blink, facial twitch, or large muscle effects such as caused by a sneeze or cough. Filtering is the primary means of reducing or eliminating these effects; however, some artifacts always manage to pass through existing systems. Artifacts can even result from the generation of "extraneous electrical potentials" from skin to electrode galvanic effects, Electromagnetic Induction (EMI), and static discharge. The majority of these types of artifact can be detected by examining the graphic records of the ongoing EEG by someone trained in their detection. When these artifacts do occur, they usually seem to be of a greater amplitude than the measured signal and, for that period of time, the measured signal will be lost in the electrical pulse of the artifact. Depending on the placement of these artifacts (for example an eyeblink may be in the range of 0.75 second duration) an entire epoch can be lost. This loss may be due to the complete overwriting of the EEG signal or may be due to the effect known as ringing. It appears that the component most responsible for this loss of information is the steep slope onset part of the artifact (personal communication C. Mann, UCLA, 1993). Regardless of which component causes this masking effect, the question remains of what to do with the loss of data. One solution is to substitute a section of artifact free data, however, this entails difficulty of insertion and substitution of data from an appropriate source. Another procedure is the use of windowing that uses a filtering system which provides a normal distribution-like filter to the dropout area. This is actually like a weighting network which diminishes the effect of the pulse by cutting out the component which is most responsible for the distortion. Essentially what this is accomplishing is further bandpass filtration on an individual EEG signal interval area. Multiple windowing is an extension of this process which smooths out the "extraneous" pulse and closes the gap caused by the artifact. Examples of artifacts can be seen in Figure 21 (Courtesy M.B. Sterman, UCLA/VAMC, 1993). Figure 21 shows the artifact from an eyeblink compared to the artifact which would result from an eye movement.



Top EEG record shows an eye blink, while the lower EEG record from the same subject shows the artifact produced by an eye movement.

Figure 21 Sample EEG signals With Two Types of Artifact

Figure 21 is also indicative of attenuation which might accompany some type of filtration of the EEG signal. In other words, any perturbation to the data can be modified or reduced, but, at this time, its effect cannot be entirely removed.

Variance of Brainwave Output

The waveform of the EEG signal is not uniform in amplitude, nor sinusoidal in frequency which limits its ability to be analysed in comparison to a signal like common alternating current. Swenson and Tucker (1983) discuss the use of several multivariate methods to assess this individual variation in what they call individual "patterning" and arousal. They used 1 second epochs which were "conditioned" with a split bell cosine function, which modified the first and last 12.5 percent of the epoch in the same way that windowing addressed artifact reduction in the previous section of this report. Their data were Fast Fourier Transformed using a Cooley and Tukey procedure for the normal delta, theta, alpha, and beta bandwidths. These cross spectra were then smoothed across 30 epochs to create a coherence matrix per band per condition per session per subject.

Cross-spectra matrices were then subjected to a factor analysis procedure using Varimax orthogonal rotation then obliquely transformed with a Promax solution (k=3). While the Promax rotation emphasized the largest loadings, the Varimax solution paralleled the Promax and commonly resulted in three factors. The Varimax rotation is an algorithm which transforms the initial correlation matrix into an easier to interpret form. It does this by rotating the axis of the ploted variables 90 degrees, in effect providing a more systematic way of looking at how the factors are related to each other (an orthogonal rotation assumes that factors are uncorrelated). Using the Promax approach, the matrix is rotated obliquely which assumes that the variables may be correlated, however, in this case both types of Factor Analysis arrived at the same conclusion; there were three primary factors which should be considered.

Two types of coherence analysis were performed on the data, multiple coherences (similar to a regression R squared) and partial multiple coherences. Multiple coherences are normalized covariances for a frequency band between one channel and all others measured. Partial multiple coherences are the spectral covariances between a subset of channels and a residual variance in a particular channel. This assumes that there is a partialing out of effects in that channel from the subset of channels previously mentioned (i.e., the subset is held constant).

Results of the previous computation showed a correlation of factor loadings and an index of homologous factors per subject, over two sessions that gave values above 0.9. There was variation in this study and it was found that frontal electrodes had particularily high values in relation to temporal electrodes. T-tests were performed on electrode by bandwidth combinations and, for nearly all combinations, significance was found at $p = .02$ or below. Some of the T-tests produced p values in the .005 range and are discussed in detail in Swenson and Tuckers text.

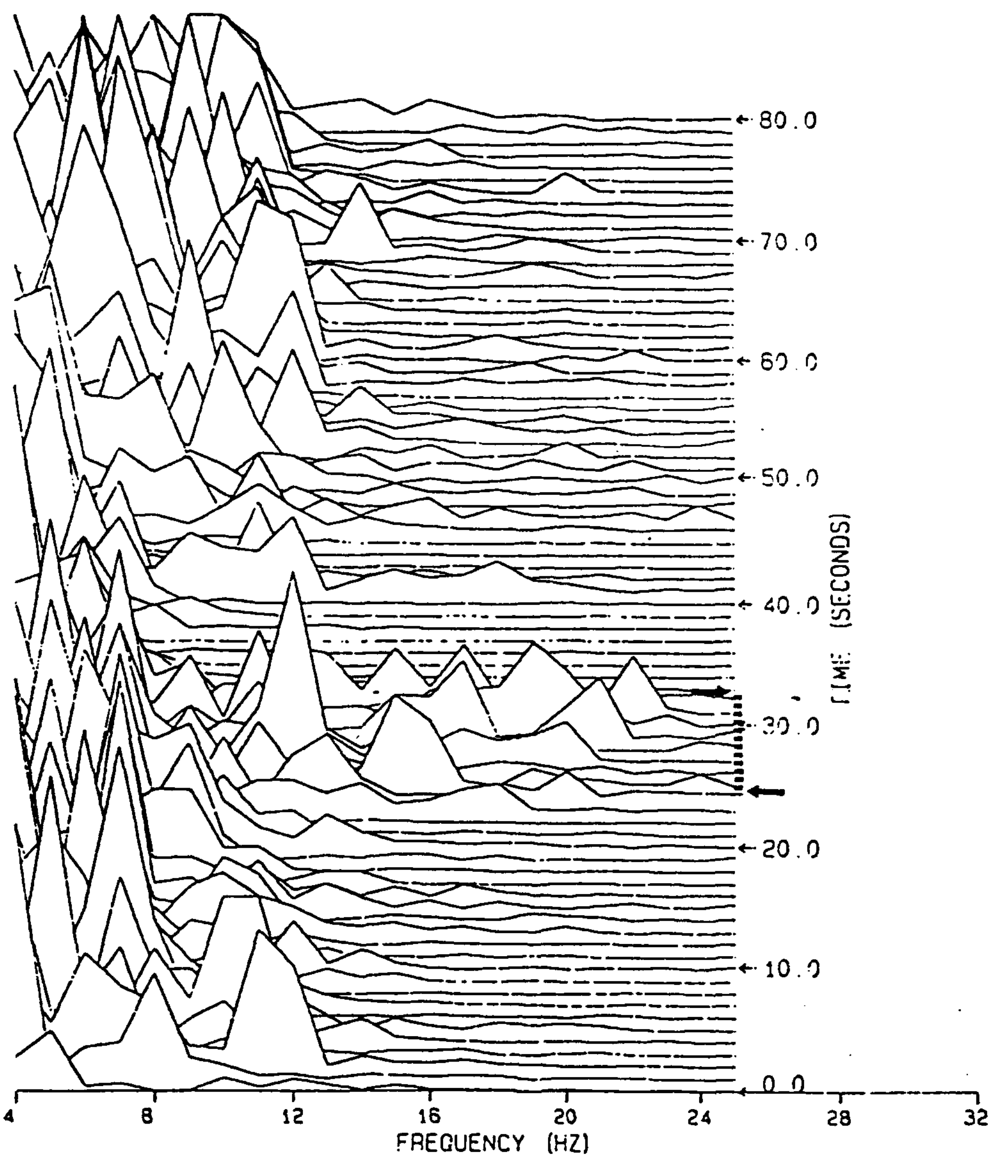
The overall consequence of this type of testing is that there are established techniques which indicate that EEG output by an individual is consistent over trials and conditions. This also applies to coherence within different bandwidths, which have degrees of variation but still provide redundant measurement information. At its ultimate extreme this could lend credence to single-site monitoring within selective bandwidths.

Analysis of Spectrographic Data

The interpretation of spectrographic data derived from EEG analysis has previously been discussed using conventional statistical methods, i.e., ANOVA, Correlation, Regression, etc. Data from spectrographic measurement methods may be represented using three-dimensional plots. These plots resemble a topographic land map with contours, peaks, ridges, and valleys. For the purpose of this report, the use of the term topgraphy applies to both the physical location of the signal within the brain (site location) as well as the three dimensional representation of spectrographic data values, therefore, topographic analysis can apply to both brain location and the topography of spectrally created EEG landscapes.

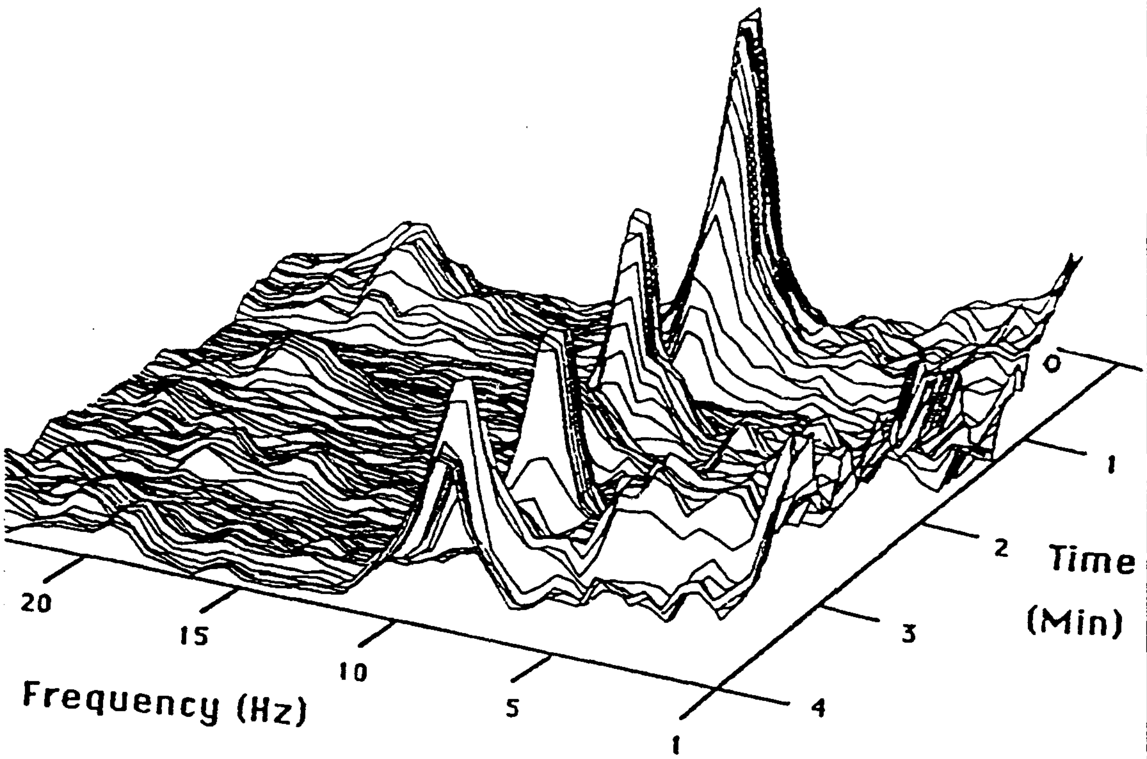
Some of the data associated with spectrographic analysis are produced from FFT transforms and are illustrated in Figure 22. This figure (from, Lewis, McGovern, Miller, Eddy, and Forster (1988)) shows the effect of a G load onset (in a centrifuge) in the frequency range from 4 to 24 Hertz over a period of time of under 10 seconds. The spectral landscape reveals clearly that something is occuring in the 25 to 31 second timeframe. This is particularily noticeable in the 12 to 24 Hertz band and shows up as a ridge of amplitudes extending out from the range to the left. It is also interesting to note that this chart shows the effect of G-LOC at the point of 31 seconds, where output drops off in those bandwidths completely until 40+ seconds. This type of presentation is more of a visual aid than a numeric index of load, in this case G-load, however, it illustrates the point that EEG signals can be displayed and visually analyzed with reasonable effect given certain assumptions.

Topographic mapping using a three-dimensional representation of the FFT transform is shown in Figure 23 from Pigeau, et al.(1988) and demonstrates the amplitude effects in a 1 to 25 Hertz band over a period of time of 4 minutes. This was from a fatigue study which examined EEG output after extended sleep deprivation periods. This particular chart shows a subject who falls asleep three times during the 4 minute session. Notice that there are four alpha peaks when the subject is awake and three alpha valleys when the subject is asleep. There also appears to be a trend toward declining alpha with the passage of time. The importance of this chart is not in



This spectrographic landscape shows increased activity in the 12 to 24 Hertz range (possibly muscle tensing) when approaching a G-LOC flight situation. The band from 8 to 24 Hertz has very little activity past the 31-second mark, the point which corresponds to the highest level of G force sustained, and the point where conciousness was lost.

Figure 22 Topographic Landscape Showing G-LOC



This representation shows three valleys between four peaks of declining amplitude over time. The data are from a sleep deprived subject who experiences three short periods of sleep as shown by three valleys located between four peaks in the 10 Hertz range.

Figure 23 Topographic Landscape Showing Sleep Onset

the characterization of alpha band versus sleep it is in the style of graphic presentation of the data and how that presentation was created. Pigeau's group used an AutoFFT method for their presentation of data. Using multiple FFTs with a window of 20 seconds and a lag of 2 seconds over a 4 minute test period they performed overlapped FFTs which resulted in 111 frequency spectra which were plotted three dimensionally. Pigeau's data from time 0 to time 20 seconds was Fast Fourier Transformed, then the timeframe 2 to 22 seconds was transformed, and this multiple FFT "windowing" process then eliminated the discontinuities which occur when digital data are "onset" and "ended." Use of this technique provided seamless data recording and interpretation possibilities with that EEG test scenario.

Statistical Analysis of Topographically Represented Spectrographic Data

There is considerable potential in the use of three-dimensional representation of spectrographic EEG data by means such as those shown in Figures 22 and 23. Representation of EEG in this way can be tied to one or more types of discrete events and also allows a characteristic pattern, like as baseline, to be created for each individual tested. What is being proposed is more like a brain-scape, or topographic representation of an individual's response pattern in simulated three-dimensional space. Figures 22 and 23 show time, frequency, and magnitude. Similar charts for different degrees of workload could also be produced using proper time synchronization to differing levels of difficulty by bandwidth and site. This process could then produce brainscape templates which could be compared within a subject to quantitatively determine control limits for any given task. This analysis concept hinges on several major assumptions:

1. The brainwave pattern for an individual is fairly constant.
This is emprically supported by studies such as Swenson and Tucker (1983).

2. The EEG trends such as Alpha suppression are repeatable and reproducable in a variety of circumstances. Empirical support for this extends back to Berger (1930).

3. There is some quantitative way to prove, with a reasonable degree of statistical confidence, that one pattern is different from another, i.e. the pattern from 1 degree of workload to another. Evidence for this could be the reliance on performance and subjective data, as well as the appropriate statistical and experimental methodology.

The first two assumptions are supported by literature review and research while the last assumption is dependent on future research.

In terms of the analysis of these spectrographic brainscapes there are sophisticated techniques which may be adapted to this type of data. Several techniques which should be explored involve the study of trend surface analysis methods. Specifically, the use of polynomial regression was proposed by Student, in 1914, to model data in two plus dimensions. This technique would be a start, and with the use of computer modeling a spacial analog of splines could also be used to model the structure of the data. A recent technique developed by D.G. Krige treats the data as a Gaussian random process then catagorizes regionalized variables by their covariance structure. Conversely, if the data are not appropriate for the formal assumptions of a Krige Model then an alternative process might be employed. An alternative might be the use of Hermite polynomials (disjunctive Kriging) which have nonexplicit distributional assumptions. It is anticipated that the previous method would provide an analysis tool which is analogous to a distribution free (nonparametric) test. Using sampling theory methods and a spacial variogram approach, the structure of the EEG topography could be explored and hypothesis testing could be possible.

CONCLUSIONS

Considerable effort has been expended in the search for quantifiable workload metrics. Of the methods proposed, EEG physiological measures offer some unique, non-intrusive and powerful techniques. Evoked Potential technology led the way for brain research from the 1940's into the late 1980's, however, in a flight test environment more powerful techniques are being developed. *Propose the use of continuous EEG measurement methods to assess workload. (R1)*[1] The challenge for EEG measurement at this time is not so much the acquisition of the signal but the analysis and modeling of that signal for predictive workload experiments. A critical issue is also whether EEG signals will correlate well with constructs representing workload. Considerable effort will be necessary to create a model which will predict overall workload and break down physical versus mental components and then be able to sucessfully discriminate sensory, mediational, and motor elements. The use of different 10/20 located sites may provide the tools to assess behavior based on known physiological functions of specific brain areas.

All of the analysis methods discussed will have to be systematically tested and only with considerable replication can this data be generalized to the general population of pilots and aircrew, and eventually to the population as a whole. At the AFFTC we have the ability to structure flight simulator workload conditions of our test subjects with a fair degree of precision, but our approach must be robust to transition to an actual flight test environment, and eventually to the general population. Currently there is a

[1] Numerals preceded by an R within parentheses at the end of a sentence correspond to the recommendation numbers tabulated in the Conclusions and Recommendations section of this report.

trend of non-mathematical and non-robust methods being used to analyze EEG data and this problem may be addressed by rigorous application of mathematical techniques. *Recommend the use of Spectrographic/Topographic methods and associated statistical analysis. (R2)*

The following factors may be considered as practical guidelines when considering the progression of an EEG test program, in a flight environment.

1. Consider the overall fidelity of flight simulation versus flight. *Tasks in a simulator environment should mirror the tasks of an inflight environment as much as possible. (R3)*

2. Establish firm control of "extraneous" variable effects both in simulator and inflight and ensure continuity within the test team and the pilots. *The pilots used for the simulator test should be used in the flight test , thus using the pilot as his own control. (R4)*

4. Budget for the analysis of large amounts of data for either flight scenario.

5. Examine the limits of the generalizability of the results derived from the various test types.

The prior considerations for EEG testing may be further addressed by some additional validity checks used in the experimental design chosen. In other words, in order to determine if we are actually measuring "workload" accurately we should include two alternative tools to enhance EEG results:

1. Aircrew subjective report using interview, written narrative, and rating scale assessment.

2. Aircrew performance measures analyzed with a critical statistical approach.

Subjective reporting should involve short, simple questionnaires which will address task situations and will be completed postflight. The use of SWAT, TLX, and Modified Cooper-Harper, and the AFFTC Modified USAFSAM scale should be used to assess subjective responses. Interviews can be informal or formal following the flight to assess the pilot's reaction to the task, assessment of workload, and performance.

Aircrew performance must be determined by using apriori criteria that involve the performance of the task; examples of this could be flight path deviations, airspeed maintenance, landing glideslope accuracy, etc. These performance tasks could then be compared to a standard type of psychological taxonomy used in workload assessment. A common taxonomy would include sensory, mediational, and motor dimensions. Combinations of these dimensions could be assessed using a task analytic approach and integrated into the flight test scenario. In time, each pilot will create enough data from test to show characteristic performance patterns which can be used to determine performance deviations under various workload conditions. Using conventional statistical procedures, the performance for all catagories of workload can be established and then correlated with self-reported workload ratings and EEG assessments. Using this multidisciplinary approach will allow comparisons of known techniques such as subjective assessment and objective performance data with the proposed EEG measures. *Use additional workload measures to confirm the results of the EEG data. (R5)*

Future Trends

Since the human brain is very capable at pattern recognition and classification, the use of graphic three-dimensional portrayal of EEG data provides the chance to rapidly assess a particular EEG data set and discriminate activities when they are correlated to time-fixed behaviors. The quantification of that type of data can be addressed by several of the analysis methods discussed previously. A detailed statistical analysis of the topographic representation of three-dimensional data is beyond the scope of this text. There are few procedures to discriminate degrees of correlation or coherence between topographic structures and some of these were reviewed previously. In other words, the ability to statistically describe onset rates, frequencies, and amplitudes simultaneously across all bandwidths and over time is a very difficult task. What can be done is to use the human ability to integrate these disparate elements into understandable patterns, which may be of the form of general pattern recognition that may have high predictive value without having an associated statistical test of probability. This is shown clearly in Figure 23 where interpretation of the waveform can be time correlated to behaviors and subjectively assessed without the use of a statistical analysis. This procedure is commonly used in the conventional medical examination of X-Ray photographs, where recognizable patterns may be differentiated without the use of an advanced statistical procedure.

The implication of the analysis methods discussed previously is that with the use of multiple sites and bandwidths the attribution of waveform output or pattern recognition could be traced to specific neural areas previously shown, by medical studies, to be associated with certain types of behaviors. In a broad sense this could provide a road map to interpret and predict behavior by looking at certain components or bandwidths in an EEG printout. This ability goes far beyond merely predicting overall classifications such as low workload versus high workload; it addresses the ability to assess behavioral events based on EEG output. Of course, this ability will require considerable investigation to determine degrees of workload, and will also have to be correlated with subjective and performance measures to be validated.

Recently, the use of automated techniques, specifically computer neural networks, have been suggested as tools which could be used to unravel patterns of the EEG signal and be able to classify those patterns more quickly and effectively than the human mind.

This technology shows considerable potential, however, it entails the expenditure of very large sums of money to manage the data and to classify and code the input to those networks, which may be more appropriate to a laboratory environment at this time.

RECOMMENDATIONS

It is recommended that the AFFTC proceed with simulator and inflight EEG studies, and the following guidance should apply to that testing:

1. Propose the use of continuous EEG measurement methods to assess workload.(page 47)

Continuous EEG measures are believed to have greater potential in the analysis of real time workload assessment than ERP studies.

2. Recommend the use of Spectrographic/Topographic methods and associated statistical analysis.(page 47)

These methods appear to have potential to sensitively discriminate types and degrees of workload which may be demonstrated by variations in amplitude and frequency of the EEG output. These techniques also allow a wide range of bandwidth and epoch analysis possibilities. In addition, they have the potential for future on-line analysis as a workload gauge rather than just as a post-hoc assessment tool.

3. Tasks in a simulator environment should mirror the tasks of an inflight environment as closely as possible.(page 48)

This will allow for the control of task related and extraneous, variables, which will influence the conclusions of the test.

4. The pilots used for the simulator test should be used in the flight test also, which will use the pilot as his own control.(page 48)

This will provide experimental design control on within-subject variability, and allow for repetitive trials to determine variance of the measures taken.

5. Use additional workload measures to confirm the results of the EEG data. (page 49)

Subjective and performance measures will provide a valuable check on the validity and conclusions which can be drawn from EEG workload studies.

The analysis techniques outlined in this document would easily lend themselves to a full-scale controlled test in a simulator or flight environment. Several studies proposed for the AFFTC could use the statistical and graphical analysis techniques listed in this report, and those techniques, when supplemented by methods used by other researchers, could provide an integrated system to quantify workload.

ABBREVIATIONS

AFFTC	Air Force Flight Test Center
Ag	Silver
AgCl	Silver chloride
AEP	Auditory Evoked Potential
ANOVA	Analysis of Variance
Au	Gold
BAEP	Brainstem Auditory Evoked Potential
CDF	Cumulative Distribution Function (Analysis)
C-H	Cooper-Harper Rating scale
CNS	Central Nervous System
EEG	Electroencephalography, Electroencephalogram
EMI	Electromagnetic Interference (by Induction)
EMG	Electromyogram
EOG	Electrooculogram
EP	Evoked Potential
ERP	Evoked Response Potential
F	F-Test (statistical)
FFT	Fast Fourier Transform
Hz	Hertz (cycles per second)
MANOVA	Multivariate Analysis of Variance
MCH	Modified Cooper-Harper Rating Scale
ms	Milliseconds
mv	Microvolts
N100	EP Negative Deflection 100 msec. Post Stimulus
PCA	Principle Components Analysis
PREP	Pattern Reversal Evoked Potential
Pt	Platinum
P300	EP Positive Deflection 300 msec. Post Stimulus
Sd	Standard Deviation
SEP	Somatosensory Evoked Potential
SWAT	Subjective Workload Assessment Technique
SWORD	Subjective Workload Dominance Technique
TIM	Technical Information Memorandum
TLX	Task Load Index (NASA rating Scale)
TPS	AFFTC Test Pilot School
VDT	Video Display Terminal
VEP	Visual Evoked Potential

APPENDIX A

There are considerable numbers of windows and transforms which have been used on EEG data however, the following formulas are considered representative for a typical application.

1. The Fast Fourier Transform is calculated using the following equation, which gives the cosine and sine terms. These form the average products of the discrete sample series x[n] with discrete cosine and sine series of different frequencies. (See Dumermuth and Molinari, in Gevins and Remond), (Eds.) Handbook of Electroencephalography and Clinical Neurophysiology.

$$A[k] = 2/N \sum_{n=0}^{N-1} x[n]\cos(2\pi kn/N) \quad \text{where } k=0,\ldots,N$$

$$B[k] = 2/N \sum_{n=0}^{N-1} x[n]\sin(2\pi kn/N) \quad \text{where } k=1,\ldots,M$$

Where N= the number of equally spaced samples used.
The data x[n] may be filtered prior to the transform.

2. Discontinuities between the first and last samples which result from the periodic sampling used are diminished by the use of a weighting function. An example of this type of function is the Hanning window, which is shown below:

$$w(n) = .56 - .44 \cos \frac{2\pi n}{N-1}$$

w = frequency
N = number of samples

3. A final transform is the use of either a log transform or a moving average procedure. This is discussed by Ahlbom and Zetterberg (1976).

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